# The Growth Effects of El Niño and La Niña:
# Local Weather Conditions Matter

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## Abstract

This paper contributes to the climate-economy literature by analysing the role of weather patterns in influencing the transmission of global climate cycles to economic growth. More specifically, we focus on El Niño Southern Oscillation (ENSO) events and their interactions with local weather conditions, taking into account the heterogeneous and cumulative effects of weather patterns on economic growth and the asymmetry and nonlinearity in the global influence of ENSO on economic activity. Using data on 75 "teleconnected" countries over the period 1975-2014, we provide evidence for the negative growth effects of ENSO events and show that there are substantial differences between its warm (El Niño) and cold (La Niña) phases and between climate zones. These differences are due to the heterogeneity in weather responses to ENSO events, known as teleconnections, which has so far not been taken into account by economists, and which will become more important in the climate-economy relationship given that climate change may substantially strengthen long-distance relationships between weather patterns around the world. We also show that the negative growth effects associated with these teleconnections are robust to the definition of ENSO events, to the use of alternative climatic variables and more important over shorter meteorological onsets.

## 1. Introduction

The last few years have seen a spate of papers analyzing the effects of long-distance relationships between weather patterns around the world, commonly referred to as teleconnections. Not only the climate literature has provided insights concerning their role in increasing the likelihood of extreme weather events (Vicente-Serrano et al., 2011; IPCC, 2019), but research in this field has also shown how climate change may strengthen their occurrence and their magnitude (Power and Delage, 2018; IPCC, 2019). Among teleconnections, El Niño Southern Oscillation (ENSO) is the most important coupled ocean-atmosphere phenomena that alters the weather conditions of distant parts of the globe. Its warm phase (El Niño) is associated with a band of warm ocean water that develops in the central and east-central equatorial Pacific while its cold phase (La Niña) is characterized by below-average Sea Surface Temperatures (SST) in the eastern Pacific. The ENSO cycle, including both El Niño and La Niña, causes global changes in temperature and rainfall on average every two to seven years which, in turn, substantially influence economic activity. Given that global warming could play an important role in the rise of teleconnections' strength and of extreme weather events related to ENSO (Cai et al., 2015; Fasullo et al., 2018; IPCC, 2019),[1] providing a well-identified understanding of channels through which ENSO affects economic performance may be essential for assessing the potential economic implications of climate change.

Although ENSO events have been observed throughout time and identified by historians as exacerbating economic and social disasters (Parker, 2013), they have only recently been taken into account by economists. As a consequence, the literature focusing on the economic impacts of ENSO is still developing. Some studies examine whether ENSO influences economies around the world,[2] with the evidence generally suggesting that it does. Estimating several vector autoregressive (VAR) models, Brunner (2002) found evidence of ENSO effects on growth and inflation in the G7 countries. Since this seminal paper, only two studies have explored the relationship between ENSO and economic performances from a multi-country perspective (Cashin et al., 2017; Smith and Ubilava, 2017). Cashin et al. (2017) estimate a Global VAR model covering 21 countries/regions over the period 1979Q2 to 2013Q1 and show that El Niño events have a direct effect on economic activity for those countries that are at the epicenter of an El Niño event (Australia, Chile, Indonesia, New Zealand, and Peru). The study also highlights important indirect effects on economic growth, inflation and commodity prices through trade and financial channels for countries that are geographically more distant

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[1]The relationship between changes in global temperatures and ENSO has also been highlighted by Parker (2013). In his book, he documents that during the little ice age period (around 1550-1700), twice as many El Niño episodes were observed. Moreover, he stresses the potential causal role of this period of prolonged cold in the higher occurrence of wars, civil wars and rebellions compared to any previous or subsequent age.

[2]Most research has been conducted using data from a single country. See for example Berry and Okulicz-Kozaryn (2008) who analyze the relationships between ENSO, U.S. inflation and economic growth over a long time span and studies focusing on ENSO effects on domestic agricultural sector (Dilley, 1997; Naylor et al., 2001).

from the phenomenon. Smith and Ubilava (2017) analyze the effect of this atmospheric phenomenon in 69 developing countries on growth rate and agricultural value-added using both linear and threshold panel regressions. They show that El Niño events have negative impacts on economic growth while the effects of La Niña events are much less significant. Their results also indicate that important regional heterogeneities exist when it comes to ENSO shocks, with stronger evidence of El Niño growth effects in tropical countries.

While these studies have provided an understanding of channels through which ENSO can directly influence economic growth, including real prices of primary commodities (Brunner, 2002), trade (Cashin et al., 2017), or agriculture share in total output (Smith and Ubilava, 2017), insights concerning the role of weather patterns as major pathways by which ENSO events may affect economic growth have not yet been integrated into econometric studies. The climate literature has, however, shown that ENSO events have large scale and regional impacts on weather patterns and seasonal climate averages (Poveda and Mesa, 1997; Vicente-Serrano et al., 2011). Based on these findings, not only the global effects exerted by ENSO on economic growth should be considered, but also its specific growth effects channeled through countries' hydro-meteorological conditions. Indeed, ENSO influences climate variability at a global scale with large differences in spatial patterns while countries' weather conditions have important effects on economic performances (Dell et al., 2014). It is then likely that the most vulnerable countries to climate hazards will also be more affected by an ENSO event. Moreover, ENSO signals may have localized impacts that cannot be reflected in economic growth without explicitly taking into account their impacts on countries' weather conditions. Finally, each ENSO event is different and occurs in conjunction with other climatic events (Davey et al., 2014). The corollary is that distinct ENSO episodes recording identical SST anomalies may be different in intensity at the regional or country level. Such temporal asymmetries may then 'mask' other important macroeconomic implications of ENSO shocks (Smith and Ubilava, 2017).

In the light of this, we contribute in this paper to the economic literature by analysing the role of weather patterns in influencing the transmission of global climate cycles to economic growth. More specifically, we focus on ENSO events and their interactions with local weather conditions, taking into account the heterogeneous and cumulative effects of weather patterns on economic growth and the asymmetry and nonlinearity in the global influence of ENSO on economic activity as discussed in the climate literature (Vicente-Serrano et al., 2011; Kumar and Hoerling, 2003; Poveda and Mesa, 1997). The inclusion of weather variables in panel estimation makes it possible to control for strictly exogenous time-varying and country characteristics, thereby ruling out any bias resulting from endogeneity.[3] Moreover, given that ENSO shocks are only slowly

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[3]Since ENSO events or weather patterns measure different aspects of climate, they are strictly exogenous. Papers estimating the ENSO growth effects can, however, suffer from another econometric problem. Indeed, given their strong correlations with ENSO and economic growth, the omission of weather variables can generate a potential source of omitted-variable bias.

absorbed by the economy, we supplement our analysis by considering their role in affecting total factor productivity.

We use the usual ENSO regime categorization that defines El Niño (La Niña) regimes by positive (negative) values of SST anomalies together with a finer classification according to the duration and the magnitude of SST anomalies. To assess weather conditions, we draw on the Standardized Precipitation and Evapotranspiration Index (SPEI) developed by Vicente-Serrano et al. (2010). This indicator incorporates both precipitation and temperature data of current weather conditions, plus their cumulative patterns of previous months. This multi-scalar feature captures medium to long-run effects of changes in weather patterns, as discussed by Dell et al. (2014),[4] and therefore allows us to identify the delayed economic impacts of ENSO through the present and past weather conditions in each country. As the weather response to ENSO events typically depends on climatic conditions, our empirical model allows for a differential effect of ENSO shocks according to the type of climate regime that prevails in each country of our sample.

Using data on 75 "teleconnected" countries over the 1975-2014 period, we show that ENSO events have heterogeneous impacts on economic activity depending on the type of climate. We also highlight that the observed disparities are explained by the heteregeonous and delayed impacts of ENSO on weather patterns across countries. In particular, El Niño phases have a delayed negative effect through drier conditions in already dry areas located in the tropical sphere. In contrast, wet parts of the arid/temperate zone are negatively affected by La Niña events, the year following their occurrence, through increased pluvial periods. These findings are highly robust to the use of an alternative categorization of ENSO regimes, of different climatic variables, and of weather conditions at different time-scales as well as across estimation methodologies.

The rest of the paper is organized as follows. To set the stage, Section 2 begins by describing the data set and presenting some stylized facts. Section 3 lays out the empirical methodology and benchmark results. In Section 4 we provide evidence for the robustness of our results when accounting for ENSO extreme events and the possible influence of the duration of weather patterns. Finally, Section 5 offers some concluding remarks.

## 2. Data and stylized facts

Our sample consists of 75 "teleconnected" countries that is, countries that are directly affected by ENSO (Hsiang et al., 2011).[5] Our panel data is unbalanced with data spanning from 1975 to 2014.[6] The sample

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[4]Dell et al. (2014) stress that the intensification issue remains a challenge and could be addressed by using a statistical approach where weather variables are interacted with their own lags or by using more advanced climate indices that reflect cumulative effects of weather shocks.

[5]See Table A.1 in the Appendix for the list of countries.

[6]The year 1975 is used as the starting date since the ENSO properties and dynamics have changed over time (Aiken et al., 2013), with lower frequency and stronger amplitude since the late 1970s (An and Wang, 2000).

includes low-income, lower-middle-income and upper-middle-income economies as classified by the World Bank.

## 2.1. ENSO phases and weather conditions

One of our main variables of interest, the measure of ENSO events, is taken from the National Oceanic and Atmospheric Administration (NOAA) of the United States dataset, which provides monthly data on the Oceanic Niño Index (ONI) from 1950 to 2018.[7] The underlying methodology used to derive these series consists of three steps. The average SST is calculated for each month in the Niño 3.4 region, spanning from 170°W - 120°W longitude and 5°N - 5°S latitude, and then averaged with values from the previous and following months. This running 3-month average is compared to a 30-year average of the three most recent complete decades, updated in each new decade. The observed difference from the average SST in that region corresponds to the ONI value for that 3-month season (i.e., the 3-month mean SST anomaly). Following Hsiang et al. (2011) and Sarachik and Cane (2010), ENSO phases are identified by averaging ONI values between the month of May of a given year and the month of February of the following year, i.e. the period over which the El Niño and La Niña events are typically most active. Positive (negative) values of the ONI reflect warming (cooling) SSTs prevailing during El Niño (La Niña) phases (Figure 1).[8]

Although annualized series reflecting SST anomalies are the most straightforward measures of ENSO, they may fail to identify the different types and intensities of El Niño and La Niña events. Recent studies have shown that the duration of and the intensity with which ENSO events propagate throughout the globe are crucial to identify their teleconnection patterns.[9] In particular, depending on their duration and their intensities, El Niño and La Niña events may be moderate or strong and thus significantly different from the neutral regime in which weak events prevail. Therefore, the real impacts of ENSO may not be adequately detected through SST anomalies captured by positive and negative values of the ONI variable.

To deal with this issue, and for the sake of robustness, we define a categorical variable reflecting each state of ENSO following the standard decision process in determining moderate to strong ENSO events as proposed by the Climate Prediction Center.[10] El Niño episodes are defined by an Oceanic Niño Index 1°C warmer than normal for at least five consecutive overlapping 3-month seasons. La Niña episodes arise when the Oceanic Niño Index is 1°C cooler than normal for at least five consecutive overlapping 3-month seasons (Figure 1). Beyond these thresholds, ENSO events are seen as moderate or strong. ENSO episodes that do

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[7]We use this index because it corresponds to the operational definition used by the NOAA. Moreover, this index has a strong correlation with both the Niño 3.4 index and the surface atmospheric pressure-based Southern Oscillation Index (SOI) (Bamston et al., 1997), which also explains its widespread use in the literature. See Table A.2 of the Appendix.

[8]ONI series are taken from the R "rsoi" package : https://github.com/boshek/rsoi

[9]See Trenberth (1997) for a detailed discussion of the different definitions of ENSO.

[10]The Climate Prediction Center is a branch of the National Weather Service of the United States.

not fall in these two categories correspond to weak events and are thus considered as neutral. El Niño and La Niña episodes categorized as weak, moderate, or strong in our sample period (1975-2014) are reported in Table 1.

**Figure 1: Evolution of the Oceanic Niño Index since 1975 (°C)**
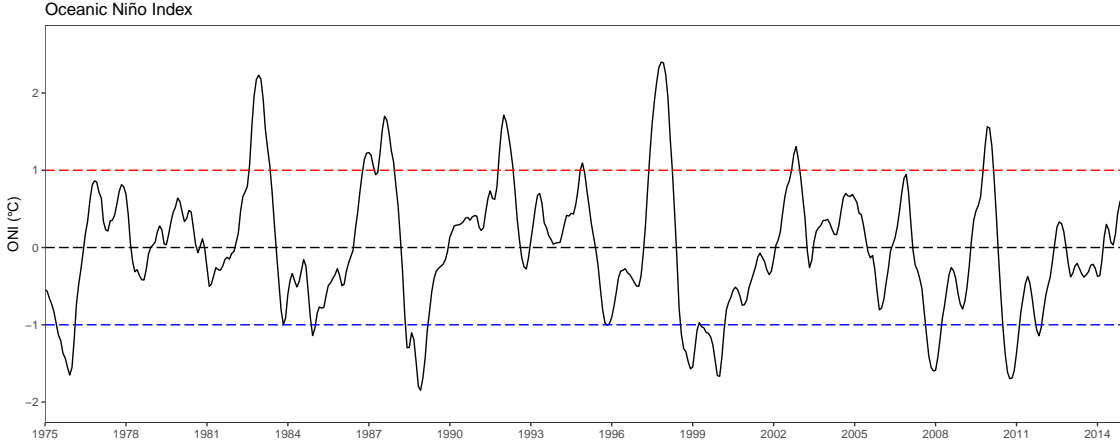


*Note: The red (blue) line indicates the threshold SST of +1°C (-1°C) that categorizes the ENSO phase as El Niño (La Niña). Source: monthly data from NOAA.*

**Table 1: Years characterized by weak, moderate, and strong ENSO events**

| | El Niño | | | La Niña | |
|---|---|---|---|---|---|
| Weak | Moderate | Strong | Weak | Moderate | Strong |
| 1977 | 1994[a] | 1987 | 1983 | 1995[a] | 1975 |
| 1979-80 | 2002[a]-2003[a] | 1991 | 1984 | | 1988 |
| 2004-05 | 2009 | 1992 | 2000-01 | | 1998-1999 |
| 2006-07 | | 1997 | 2005-06 | | 2007 |
| 2014 | | | 2008-09 | | 2010-2011 |

*Note: [a] Years characterized by events of lower amplitude but reported by NOAA as having significant repercussions.*

We select the Standardized Precipitation and Evapotranspiration Index (SPEI) to capture weather variation that may be affected by ENSO shocks. The SPEI is based on a climatic water balance and therefore accounts for the combined impact of temperatures and precipitation using changes in potential evapotranspiration demand which is expected to be important to capture the influence of the ENSO phenomenon on the climate-agriculture relationship (Vicente-Serrano et al., 2011). We then calculate monthly averages of the SPEI at the global scale, with a 0.5 degrees spatial resolution based on the FAO Penman-Monteith evapotranspiration equation.[11] The SPEI is also relevant for the analysis and the assessment of time-varying

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[11]We use data from the Climate Research Unit (CRU) on climatological records of solar radiation, air temperature, rainfall, humidity and wind speed to compute the FAO Penman-Monteith evapotranspiration equation and the climatic water balance. See Appendix B.1 for more details regarding the computation of the SPEI.

economic risks at a large geographical scale. Given the strong seasonal differences in the magnitude of temperatures and precipitations, climatic water balance series are transformed using equal probability to a normal distribution so the values of the SPEI are comparable in time and space.[12]

Positive (negative) SPEI indicates wetter (drier) hydro-climatic conditions.[13] Another advantage of the SPEI is that it can be calculated at various time scales (between 1 and 48 months) over which water deficits/surplus accumulate reflecting the different response times of hydrological and agricultural systems to weather conditions. This multi-scalar feature allows us to take into account the structural effects of ENSO that depend on the crops' response, natural vegetation, and hydrological systems. Furthermore, using time scales representing short to medium term dry or wet spells helps us to identify the lags that commonly occur in the response of weather conditions to ENSO events. Indeed, El Niño and La Niña phases exert differing impacts depending on the hydrological cycle (Penalba and Rivera, 2016), and in turn, their economic impact can be exacerbated by the weather prevailing in previous months. The SPEI constitutes, therefore, an efficient way to address the intensification process of climate effects by taking into account the time structure of weather shocks in the economic response to ENSO events. We use as a benchmark indicator the 6-month SPEI, given its ability to capture seasonal to medium-term trends in weather conditions that mainly affect agricultural systems; but also show the robustness of our results using the 3-month and 12-month SPEI.[14]

A key challenge of using weather indicators is to aggregate gridded SPEI observations in order to obtain indexes consistent with economic data and reflecting adequately the climate variability experienced by each country. The procedure of averaging gridded weather data at the country level leads to loss of relevant information for two main reasons. First, changes in temperature, precipitation, and other climate parameters usually vary within countries, with differential exposure and uneven consequences at the local level. Ignoring this scale-dependency issue can be problematic as extreme conditions at the local level are likely to be obscured by using averaged data at the country level, and lead to a biased assessment of weather conditions. Secondly, this approach could fail to identify climate shocks affecting human activities especially if large areas where little economic activity and sparse populations dominate, such as deserts or rain forests (Dell et al., 2014). To deal with this problem and to derive consistent country-level series, we assign individual gridded SPEI values over cropland areas to individual countries to arrive at country-wide time series. Restricting weather conditions to cropland areas has several advantages. It provides a framework for delimiting relevant areas for natural and human systems and where the deleterious impacts of climate shocks are generally

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[12]We also use alternative indicators of weather conditions such as air surface temperatures anomalies and rainfall anomalies for the sake of robustness. See section 4.2.

[13]Different intensities in hydro-climatic conditions can be identified, according to threshold values reached by the SPEI, as detailed in Table B.1 of the Appendix.

[14]The resulting time series of 6-month SPEI are shown in figure B.3 in the Appendix.

considered to be greatest (Deschênes and Greenstone, 2007). Therefore isolating the component of climate variability in cropland areas allows us to identify one of the main sources through which climate shocks affect economic growth. Another advantage of this aggregation approach is that it provides a consistent measure of climate variability within a country as cropland areas broadly share the same weather conditions. To retrieve the climate variability in cropland areas, we rely on the Global Land Cover SHARE (GLC-SHARE) prepared by FAO's Land and Water Division (NRL). This database provides information on mainland use and land cover shares, on each 1 by 1-kilometer plot of land covering the entire globe. We construct monthly SPEI values at the country level by overlaying grid cells of SPEI over cropland distribution in each country and averaging the SPEI values over each country's arable and permanent croplands.[15]

### 2.2. Identifying climate groups

To capture the variability of ENSO impacts across countries, with some regions considered more "teleconnected" to ENSO (continental tropics) than others (mid-latitudes regions), we partition the globe into two groups − tropical/humid and temperate/arid countries according to the Köppen-Geiger Climate Classification (Kottek et al., 2006). However, in order to have country groups consistent with SPEI values calculated at the country level, we identify climatic conditions which only prevail in cropland areas within each country. Specifically, we define tropical/humid countries as those with 50% or more of their total cropland areas falling into the four subtypes of tropical climates.[16] Countries having a temperate/arid climate refer to those with 50% or more of their total cropland area characterized by one type of arid or mild temperate climates.[17] The list of countries included in each of these two climate groups is provided in Table A.1 of the Appendix.[18]

The widespread influence of ENSO events on local weather patterns is shown in Figure 2 which reports SPEI anomalies, defined as the difference between the SPEI values prevailing during normal conditions and those prevailing during an ENSO episode (Figure 2a). To illustrate the delayed impact of El Niño and La Niña on weather patterns, we also report SPEI anomalies during the year following an ENSO episode (Figure 2b).

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[15]See section B.2 of the Appendix for an extensive discussion on how the average SPEI for each country is constructed.

[16]i.e. tropical rain forest, tropical monsoon, tropical savannah with dry summer, and tropical savannah with dry winter.

[17]Classes of arid climates refer to desert, steppe-hot arid and steppe-cold arid while subtypes of mild temperate climates include mild temperate with dry summer, mild temperate with dry winter, mild temperate fully humid warm summer, mild temperate fully humid cool summer.

[18]The classification is close to the one used in the literature except for large countries, such as India, and Mexico.

**Figure 2: Difference between the SPEI average during El Niño (La Niña) years and neutral years (1975 - 2014)**

**(a) Immediate effect**  **(b) Delayed effect**
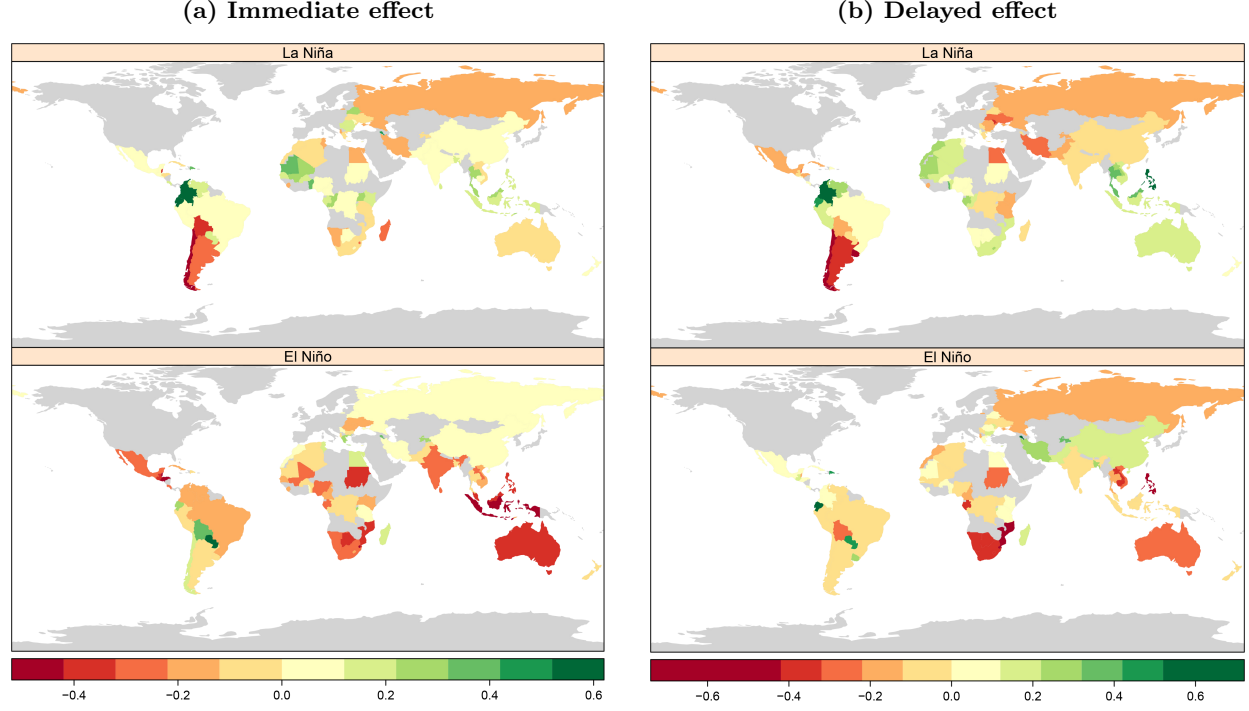


Note: Map (a) shows, for each country, the difference between the average of SPEI during the El Niño (La Niña) years and that during years characterized by a neutral ENSO regime. The delayed effect (map b) is calculated as the average difference between the SPEI the year following an El Niño (La Niña) shock and the years characterized by a neutral regime. Countries are color-coded on the basis of their SPEI anomalies: red (green) for countries with drier (wetter) conditions than those prevailing during normal conditions. Deeper is the color, higher are the SPEI anomalies.

Figure 2 shows that most countries have less precipitation during an El Niño episode. In Central America, El Niño is associated with serious drought in Mexico, Guatemala, Honduras, and El Salvador. Some Caribbean countries also suffer from drought. In addition, El Niño years lead to drought in Africa, as countries (such as Mali, Sudan, and Nigeria) tend to see lower SPEI during an El Niño event while droughts occur in the already very dry south of the continent (Mozambique, and Botswana). Moreover, other notable dry places include Indonesia, South and South-East Asia, and Australia. In general, La Niña effects on weather patterns are the opposite of those induced by El Niño resulting in wetter-than-normal conditions in Southern Africa and in the central Andes. Very heavy rain and flooding due to La Niña is also observed in the Philippines, Malaysia, Indonesia, and Australia. In contrast, many droughts are reported in Argentina, Chile and over East Africa following La Niña events. Finally, the surface extent and duration of the SPEI anomalies show that large areas of the world have SPEI anomalies lasting several months, confirming that the effects of El Niño and La Niña events on weather patterns can spread over many seasons (Vicente-Serrano et al., 2011; Kumar and Hoerling, 2003; Poveda and Mesa, 1997). One year after the occurrence of ENSO events, El Niño

still affect most of Indonesia, the Indochina Peninsula, parts of Africa, and Australia whereas La Niña leads to substantially more precipitation as compared to neutral ENSO regimes in Africa and South East Asia.

### 2.3. Real income growth and ENSO events

We use GDP per capita since ENSO has widespread economic impacts which go beyond the sole agricultural sector.[19] We obtain the series from the recent version of the Penn World Table database. In Table 2, we report the means, standard deviations, and ranges for the 6-month SPEI and the real GDP per capita growth by climate areas (tropical/humid and temperate/arid).[20]

**Table 2: Summary statistics by climate areas**

| Countries | n | 6-month SPEI | | | | Growth rates | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | mean | min | max | sd. | mean | min | max | sd. |
| All | 75 | -0.0292 | -1.772 | 2.348 | 0.5212 | 0.0167 | -0.5226 | 0.2833 | 0.0520 |
| Tropical & humid | 39 | -0.0110 | -1.772 | 2.348 | 0.5197 | 0.0165 | -0.2983 | 0.2833 | 0.0165 |
| Temperate & arid | 36 | -0.0516 | -1.559 | 1.958 | 0.5265 | 0.0168 | -0.5226 | 0.2571 | 0.0579 |

According to the mean value of SPEI and real GDP per capita growth, few differences are apparent between the two climate areas. However, given the diverse geographic and economic conditions as well as climatic variability within these two areas, it is unlikely that the means are completely homogeneous across all countries and over time, as indicated by the high standard deviations. In order to investigate this further, Figure 3 displays the distribution of economic growth according to ENSO episodes for tropical/humid and temperate/arid countries.

As can be seen from Figure 3 the contemporaneous effects of El Niño phases suggest a lower average rate of growth as compared to the neutral and La Niña phases, in line with what has been reported in the literature. The delayed response of GDP growth to ENSO events remains, on the contrary, less clear. Indeed, no distinct differences can be observed across growth averages when considering lagged ENSO events. Importantly, there is a significant dispersion of real GDP growth across countries, illustrating the strong heterogeneity in countries' responses to ENSO events. This cross-country dispersion can be explained by many factors among which weather conditions play a key role due to their heterogeneous responses to ENSO events and their differentiated effects on countries' economic growth. The following section aims to investigate this issue.

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[19]Most papers show that ENSO exacerbate conflicts (Hsiang et al., 2011), exert inflationary effects (Cashin et al., 2017), causes damage to infrastructure, etc. The lack of available data is another reason that motivates us to assess the economic growth effects of ENSO events rather than their impact on agricultural income. Indeed, the use of agricultural value-added considerably reduces the length of our series. Consequently, the period is not sufficiently long to identify enough ENSO shocks, which makes the estimates unreliable and unstable due to a highly unbalanced panel.

[20]Table A.3 in the Appendix provides a detailed overview of the variables included in our dataset.

**Figure 3: Real GDP per capita growth and ENSO events**

**(a) Tropical & humid countries**



**(b) Arid & temperate countries**
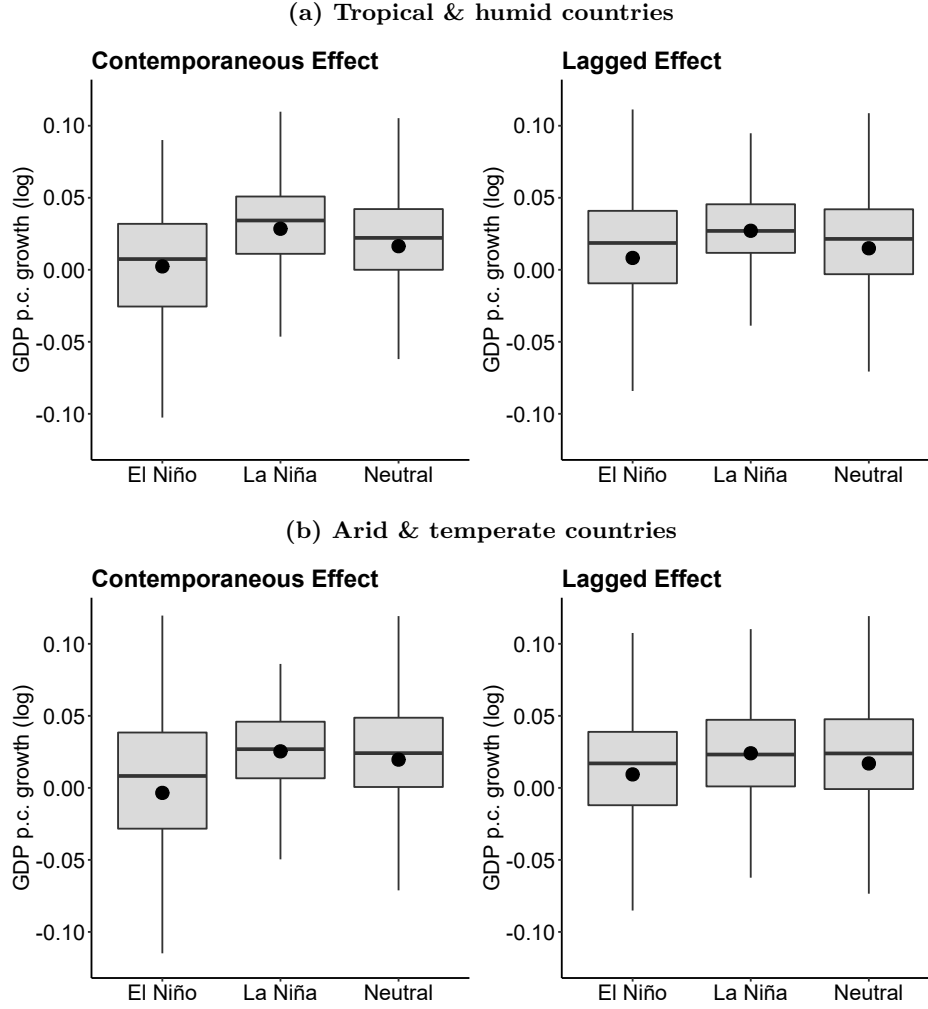


*Note: The box plots reported in the figure* show the distribution of the economic growth according to ENSO cycles for the current year (contemporaneous effect) and the year following any event (lagged effect). The ends of the box represent the lower and upper quartiles of the data. The line across the middle of the box is the median and the dot, the mean. The lines protruding from the box indicate the lowest and largest data point excluding any outliers, and thus the degree of dispersion in the data.

## 3. Empirical results

### 3.1. Econometric methodology

Since ENSO impacts can extend beyond a calendar year and may also be temporally displaced, we estimate the contemporaneous as well as the lagged growth effects of ENSO events. To test our central hypothesis, we use interaction terms to assess how ENSO events influence growth under certain weather conditions. Given

that the two climate variables, SPEI and ONI, are strongly related contemporaneously,[21] we interact the SPEI variable with the one-period lagged value of the ONI variable. Our main specification is then given by:[22]

$$\Delta y_{i,t} = \lambda + \alpha ONI_t + \beta SPEI_{i,t} + \gamma ONI_{t-1} + \delta \left( ONI_{t-1} \times SPEI_{i,t} \right) + \mu_i + \varepsilon_{i,t} \tag{1}$$

where $y_{i,t}$ is the log of real GDP per capita of country $i$ in year $t$, $ONI_t$ is a vector of variables depicting the effects of ENSO events captured by annualized ONI values in year $t$, $SPEI_{i,t}$ is a vector of weather conditions measured by the 6-month SPEI, and the interaction term, $(ONI_{t-1} \times SPEI_{i,t})$, permits us to assess whether ENSO events have a different delayed influence on growth in countries where wet conditions prevail in cropland areas than in countries where these areas are rather characterised by dry conditions.

Equation (1) imposes a monotonic relationship between ENSO events and economic growth by assuming that climate anomalies related to La Niña events can be regarded as a mirror image of those associated with El Niño events. However, the climatology literature has produced considerable evidence on the asymmetry between El Niño and La Niña events (Burgers and Stephenson, 1999; Jin et al., 2003b; An and Jin, 2004; An et al., 2005; Zhang et al., 2015) mainly due to nonlinear responses in the atmosphere to the underlying SST anomalies (Hoerling et al., 1997; Jin et al., 2003a). To address this asymmetry issue, we follow Smith and Ubilava (2017) and interact the variable ONI with a Heaviside indicator that partitions the variable ONI into positive and negative values:

$$\begin{aligned} \Delta y_{i,t} = &\left[ \alpha_1 ONI_t + \beta_1 SPEI_{i,t} + \gamma_1 ONI_{t-1} + \delta_1 \left( ONI_{t-1} \times SPEI_{i,t} \right) \right] I\left(.\right) \\ &+ \left[ \alpha_2 ONI_t + \beta_2 SPEI_{i,t} + \gamma_2 ONI_{t-1} + \delta_2 \left( ONI_{t-1} \times SPEI_{i,t} \right) \right] \left( 1 - I\left(.\right) \right) \\ &+ \lambda + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{2}$$

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[21]ENSO events generally occur between May of a given year and the month of February of the following year. Some El Niño or La Niña events may appear later in the year (around November / December) and result from weather conditions favoring the manifestation of an event. Therefore, including an interaction term between the ENSO and SPEI variables to identify their contemporary effect on economic growth does not seem appropriate given that these variables are strongly related contemporaneously. On the one hand, ENSO events exert large scale and regional impacts on weather patterns and seasonal climate averages. On the other hand, they are also explained by the climatic conditions during the months preceding their occurrence. We have estimated a specification that includes a contemporary interaction term between the ENSO and SPEI variables. Our results, available upon request, show that the coefficient on the SPEI variable becomes significant in both climate areas, while the interaction terms are less significant. This suggests that, when including an interaction term between contemporaneous variables, the coefficient on SPEI captures not only the direct effect of weather conditions on economic growth but also part of the indirect effect exerted by the contemporaneous influence of ENSO.

[22]We restrict our set of explanatory variables to climate and weather variables in order to avoid an "over-controlling problem" (Dell et al., 2014).

where $I\left(.\right)$ is the Heaviside function such that:

$$I\left(.\right) = \begin{cases} 1 & \text{if} \quad ONI_t \geq 0 \quad \text{(El Niño)} \\ 0 & \text{if} \quad ONI_t < 0 \quad \text{(La Niña)} \end{cases}$$

The standard methods of estimating ENSO events with panel data rely usually on fixed-effects models. The major drawback of these models is that they not directly address the important question of the spatial and temporal correlation of climate and weather conditions across countries. As noted by Beck and Katz (1995), coefficient estimates from standard panel estimators can be severely biased if cross-section dependence is present. A preliminary analysis of the data using OLS reveals evidence of nonspherical errors because of contemporaneous correlation across the units alongside heteroskedasticity and serial correlation.[23] This finding is not surprising given that economic activity may spill over into contiguous or economically related countries and climate events, such as ENSO, cross countries' borders (Auffhammer et al., 2013). Parks (1967) proposed to improve inference and estimation efficiency using a feasible generalized least squares (FGLS) estimator that has been popularized by Kmenta (1986). However, this estimator has been shown to exhibit poor finite sample properties, with overconfident standard errors rendering hypothesis testing useless (Beck and Katz, 1995).[24] To address these problems, we use Prais-Winsten estimates with a sandwich-type estimator of the covariance matrix developed by Beck and Katz (1995). The so-called panel-corrected standard errors (PCSE) are robust to very general forms of cross-sectional dependence as well as autocorrelated errors of type AR(1). Results from PCSE estimates are also compared with Driscoll and Kraay (1998) covariance matrix estimator for fixed effects regression. Driscoll and Kraay's methodology is consistent independently of the cross-sectional dimension $N$ and is robust to higher-order serial correlation.[25]

*3.2. Growth effects of ENSO events*

Tables 3 and 4 present the results of the regression analyses for tropical/humid and arid/temperate countries respectively. Each table includes two sets of results from PCSE and DK estimations. We first estimate equation (2) without any weather variable or interaction term between ONI and SPEI, as shown in columns

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[23]Results of this preliminary analysis are reported in Tables C.1 and C.2 of the Appendix. Results reported in Table C.2 show that, for all variables, there is strong evidence against the null hypothesis of no cross-section dependence in the model's variables.

[24]The Parks-Kmenta Feasible Generalized Least Squares estimator (FGLS) cannot be estimated when the time period ($T$) is less than the number of cross-sectional units ($N$) since the associated error variance-covariance matrix cannot be inverted. Even when $T \geq N$, Beck and Katz (1995) showed that the estimated standard errors using the Parks-Kmenta approach generate confidence intervals that are significantly too small, often underestimating variability by 50% or more.

[25]We have also tested the unit root null hypothesis in our panel data setting using the Cross-sectionally Augmented IPS (CIPS) panel unit root test advanced by Pesaran (2007), which allows for cross-sectional dependence. As is clear from Appendix Table B.3, the null hypothesis of a unit root is rejected for the variable $SPEI$. The null hypothesis of a unit root is not rejected for the level of $y$, while rejected for its first difference.

(1) and (4) of Tables 2 and 3. We find that increasing positive values of the ONI has a contemporaneous negative effect on growth in countries located in tropical/humid areas, indicating that the El Niño regime leads on average to lower growth rates in those countries. Its impact is, however, weakly significant in arid/temperate areas. This first finding is consistent with the literature (Cashin et al., 2017; Smith and Ubilava, 2017). In contrast, the growth response to La Niña events is not significant, regardless of the climate type, confirming the asymmetric nature of ENSO.

When adding the SPEI variable, we note that the effect of weather conditions is positive and significant only in arid/temperate countries, showing a high vulnerability of this climate zone to droughts. Moreover, controlling for countries' specific weather conditions does not modify the results obtained regarding the ENSO's contemporaneous effect on growth. Indeed, the negative growth effect of El Niño phases is still significant only for tropical/humid countries, while La Niña has no significant impact in both climate areas. The climate-literature provides insights into the mechanisms responsible for this asymmetric feature of ENSO. First, there is evidence that the observed El Niño is larger than that of La Niña, especially since the climate shift around the year 1975 (An and Jin, 2004). Furthermore, the overall effect of La Niña events is usually the result of more localized tropical convection anomalies than those observed during El Niño phases (Mason and Goddard, 2001), which could also account for this differentiated impact. Another explanation, well documented by the climate literature, is due to the delays in hydrological responses to ENSO events (see, e.g., Kumar and Hoerling (2003)). Accordingly, the impact of La Niña events is likely to propagate throughout weather conditions only with some delays after their occurrence.

**Table 3: Contemporaneous and lagged impacts of ENSO events**
**Tropical & humid countries**

| | PCSE estimates | | | DK estimates | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $ONI_t \geq 0$ | -0.0132** | -0.0121** | -0.0159*** | -0.0222** | -0.0213** | -0.0228*** |
| | (0.0059) | (0.0059) | (0.0061) | (0.0088) | (0.0091) | (0.0080) |
| $ONI_t < 0$ | -0.0023 | -0.0027 | -0.0050 | -0.0072 | -0.0075 | -0.0080 |
| | (0.0061) | (0.0060) | (0.0059) | (0.0065) | (0.0064) | (0.0067) |
| $SPEI_t$ | | 0.0045** | -0.0030 | | 0.0037 | -0.0040 |
| | | (0.0022) | (0.0037) | | (0.0033) | (0.0048) |
| $ONI_{t-1} \geq 0$ | | | -0.0101* | | | -0.0148* |
| | | | (0.0060) | | | (0.0075) |
| $ONI_{t-1} < 0$ | | | -0.0058 | | | -0.0073 |
| | | | (0.0057) | | | (0.0083) |
| $ONI_{t-1} \geq 0 \times SPEI_t$ | | | 0.0194*** | | | 0.0173*** |
| | | | (0.0070) | | | (0.0058) |
| $ONI_{t-1} < 0 \times SPEI_t$ | | | 0.0090 | | | 0.0126* |
| | | | (0.0074) | | | (0.0066) |
| Constant | 0.0163 | 0.0154 | 0.0209 | 0.0233*** | 0.0232*** | 0.0291*** |
| | (0.0126) | (0.0125) | (0.0128) | (0.0043) | (0.0043) | (0.0065) |
| Countries ($N$) | 39 | 39 | 39 | 39 | 39 | 39 |
| Observations ($N \times T$) | 1521 | 1521 | 1521 | 1521 | 1521 | 1521 |
| $R^2[within]$ | 0.0778 | 0.0798 | 0.0889 | [0.0200] | [0.0218] | [0.0330] |
| PSAR(1) | Yes | Yes | Yes | No | No | No |
| MA(3) | No | No | No | Yes | Yes | Yes |

*Note: Prais-Winsten (PSCE) estimates and fixed effects (within) regression models with Driscoll and Kraay (DK) standard errors. $ONI \geq 0$ and $ONI < 0$ stand respectively for El Niño and La Niña conditions. Standard errors are in parentheses. ***, **, and * indicate respectively 1%, 5%, and 10% significance levels. PSAR(1) stands for panel specific AR(1)-type autocorrelation. MA(3) denotes autocorrelation of the moving average type with automatic lag length.*

As shown in columns (3) and (6), which report the results of our specification (2), the existence of such delayed effects is confirmed. ENSO negatively affects GDP growth in both climate areas through its differing impacts on weather conditions. As can be seen, in tropical/humid areas, while the contemporaneous negative effect of ENSO remains unchanged, the coefficient on the interaction term between the positive lagged value of ONI and the SPEI is significant. This lagged impact through weather conditions can be explained by the role played by El Niño events on the occurrence of tropical droughts. Unlike other natural hazards, droughts tend to develop very slowly over time and preferentially during El Niño events in this part of the world with a linear relationship to the strength of El Niño (Vicente-Serrano et al., 2011; Lyon, 2004; Mason and Goddard, 2001). The delayed effect of El Niño events on economic growth in tropical/humid countries is thus channeled through a higher probability of drier than normal weather conditions. Accordingly, taking into account the

**Table 4: Contemporaneous and lagged impacts of ENSO events**
**Arid & temperate countries**

| | PCSE estimates | | | DK estimates | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $ONI_t \geq 0$ | -0.0143* | -0.0112 | -0.0123 | -0.0241* | -0.0212* | -0.0204* |
| | (0.0078) | (0.0078) | (0.0076) | (0.0133) | (0.0125) | (0.0119) |
| $ONI_t < 0$ | 0.0007 | 0.0031 | 0.0009 | -0.0005 | 0.0019 | 0.0007 |
| | (0.0088) | (0.0086) | (0.0079) | (0.0092) | (0.0091) | (0.0084) |
| $SPEI_t$ | | 0.0128*** | 0.0150*** | | 0.0131** | 0.0168*** |
| | | (0.0031) | (0.0056) | | (0.0056) | (0.0060) |
| $ONI_{t-1} \geq 0$ | | | -0.0095 | | | -0.0150 |
| | | | (0.0075) | | | (0.0095) |
| $ONI_{t-1} < 0$ | | | -0.0077 | | | -0.0068 |
| | | | (0.0077) | | | (0.0130) |
| $ONI_{t-1} \geq 0 \times SPEI_t$ | | | 0.0105 | | | 0.0092 |
| | | | (0.0093) | | | (0.0077) |
| $ONI_{t-1} < 0 \times SPEI_t$ | | | -0.0194* | | | -0.0226** |
| | | | (0.0103) | | | (0.0097) |
| Constant | 0.0202*** | 0.0222*** | 0.0268*** | 0.0225*** | 0.0221*** | 0.0271*** |
| | (0.0054) | (0.0054) | (0.0063) | (0.0072) | (0.0070) | (0.0091) |
| Countries ($N$) | 36 | 36 | 36 | 36 | 36 | 36 |
| Observations ($N \times T$) | 1299 | 1299 | 1299 | 1299 | 1299 | 1299 |
| $R^2[within]$ | 0.0641 | 0.0825 | 0.0952 | [0.0174] | [0.0310] | [0.0462] |
| PSAR(1) | Yes | Yes | Yes | No | No | No |
| MA(3) | No | No | No | Yes | Yes | Yes |

*Note: Prais-Winsten (PSCE) estimates and fixed effects (within) regression models with Driscoll and Kraay (DK) standard errors. ONI $\geq 0$ and ONI $< 0$ stand respectively for El Niño and La Niña conditions. Standard errors are in parentheses. ***, **, and * indicate respectively 1%, 5%, and 10% significance levels. PSAR(1) stands for panel specific AR(1)-type autocorrelation. MA(3) denotes autocorrelation of the moving average type with automatic lag length.*

delayed effects of ENSO through weather conditions suggests that El Niño episodes have a negative growth effect in dry areas of the tropical/humid zone. This effect is likely to spread over time as El Niño tends to increase the exposure of those areas to drier conditions. As shown in the sixth column of Table 3, this result is robust to DK estimates.

Results for arid/temperate countries show that the coefficient on contemporaneous El Niño events is still slightly significant (at only the 10% level) while the growth effect of SPEI remains positive and significant (column (6) of Table 4). Importantly, La Niña events have a lagged effect on growth through their interaction with weather patterns, which is essentially the reverse of the El Niño effect observed in tropical/humid countries. Indeed, by bringing higher than average precipitation, La Niña causes rainfall to become more intense and wet areas in arid/temperate countries to become wetter, which adversely affects GDP growth.

Again, this result is robust to the choice of estimator, confirming that ENSO events also significantly affect the GDP growth of arid/temperate areas through their delayed impacts on weather conditions. Overall, our results allow identifying El Niño and La Niña as important sources of nonlinearity in the growth-weather nexus. In particular, this nonlinearity – captured by the interaction terms – operates through weather anomalies that are exacerbated by ENSO events.[26]

We check the robustness of our results to different measures of income and ENSO events. For example, as an alternate measure of income, we make use of GDP per capita series from the World Bank's World Development Indicators and as another measure of ENSO, we use the Equatorial Southern Oscillation Index (SOI), calculated as the standardized anomaly of the difference between the area-average monthly sea level pressure in an area of the eastern equatorial Pacific (80°W - 130°W, 5°N - 5°S) and an area over Indonesia (90°E - 140°E, 5N - 5°S). The results with these alternative measures illustrate that no matter which measure is utilized, the interaction term between ENSO events and weather conditions remains significant and has the same sign with the same order of magnitude for both climate areas. This finding is not surprising, given the high correlation between the two GDP per capita growth series and the two ENSO indexes.[27] For the sake of brevity, the results of these robustness checks are not reported in the paper but are available from the authors upon request. Finally, we test whether our main results persist across model specifications. Consistent with the estimation approach adopted in the growth literature, we estimated equation (2) using the system GMM estimator. The results, reported in Table C.4 of the Appendix, provide clear evidence of delayed growth impacts of ENSO through weather conditions. Next, following the climate literature,[28] we run a "placebo" test by including in our baseline specification (equation (2)) leads in the weather and ONI variables to check whether the existence of economic expectations of the ENSO cycles does not invalidate our results. Indeed, ENSO events and their weather effects are the subject of a particular attention in terms of forecasting, given that they may be a significant force in orchestrating forward-looking economic and social adjustments. Even though reliable forecasts techniques for the onset and, in particular, the magnitude of ENSO events are not fully satisfactory (Meng et al., 2018),[29] it seems useful to verify whether including expectations of ENSO episodes and weather conditions may lead to a potential source of omitted-variable bias in our analysis. Results of the "placebo" test are reported in Table C.5 of the Appendix. For tropical and humid countries, the estimated lead coefficient on El Niño is negative and statistically significant, indicating

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[26]To confirm this result, we have estimated the same model with a quadratic formulation for the weather variable. The results suggest no additive weather effects, with still a significant interaction between the ENSO and SPEI variables, but without nonlinear effects associated with the quadratic component for the SPEI variable. Results are available upon request.

[27]See Table A.2 and Figure A.2 in the Appendix.

[28]See for example, Barreca et al. (2016).

[29]Difficulties in predicting the timing of ENSO events and their correct strength make predictions of its global impacts challenging since those often occur on regional scales and may be influenced by regional and/or local effects.

the adverse effect on income growth driven by expectations of El Niño future events in this climate area. The growth effect of such expectations is, however, not driven by expected adverse weather effects related to this ENSO cycle since the estimated lead coefficient on the interaction term is not significant. For arid and temperate countries, we find no significant difference in the estimates from the model including leads and the baseline specification. As a whole, this "placebo" test suggests that our main results are not driven by trends or factors that we fail to control for. Finally, we perform additional testing to include time fixed effects to control for global shocks, other than climate shocks, which might also affect aggregate growth in any period but are not otherwise captured by the explanatory variables. Table C.6 of the Appendix reports our regression results. As seen from this table, the coefficient on the SPEI variable is still positive and highly significant for arid and temperate countries. However, the coefficients associated with El Niño and La Niña are now negative and significant for both climate areas. This result suggests a serious multicolinearity problem since ENSO variables, which vary only over time, and time fixed effects may move together. The Variance Inflation Factor (VIF) and the Tolerance value reported in C.7 of the Appendix confirm that severe multicollinearity is present when time fixed effects are included. In any case, we are most interested in the explanatory power of the interaction between the ENSO and SPEI variables. The inclusion of time fixed effects does not affect the estimated coefficients of these interaction variables. Therefore, our results highlighting the growth effects of ENSO events through their delayed impacts on weather conditions remain robust.

### 3.3. Explaining the growth's response to ENSO events: the role of total factor productivity growth

Since ENSO events have diffused effects over time on weather patterns, they are only slowly absorbed by the economy and should therefore have long-lasting effects. We thus examine whether the previous results on economic growth are driven through Total Factor Productivity (TFP) growth. In order to do this, we re-estimate equation (2) with TFP per capita growth (instead of GDP per capita growth).[30]

The results in Table 5 indicate strong evidence that the ENSO events affect TFP growth through their interaction with weather patterns. The predominance of TFP growth for explaining the delayed ENSO effects on output growth is in line with other panel studies that find strong evidence of weather effects on TFP growth (Letta and Tol, 2018). Columns (1) and (4) show a less pronounced immediate impact of El Niño on TFP growth in both climate areas. Adding lagged effects of ENSO yields, however, very similar effects as the interaction terms with SPEI are still significant in both areas (columns (3) and (6)). As for economic growth, the analysis by climate regions reveals different delayed growth effects of ENSO events through their connection with weather conditions, with a predominance of negative effects of El Niño events

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[30]For the definition of TFP see Table A.3 and for the panel unit root tests for annual TFP growth, see Table C.3 in the Appendix.

in tropical/humid countries and of La Niña episodes in arid/temperate countries. The negative response of GDP growth to ENSO events is thus mainly driven by the decrease in productivity growth due to the delayed effects of ENSO on weather patterns. This finding is important as it implies that the fall in productivity growth driven by ENSO events is likely to have a negative impact on output growth in subsequent periods and possibly alter income trajectories in a permanent way, especially since it is expected that extreme El Niño and La Niña events will become more frequent (IPCC, 2019).

**Table 5: Contemporaneous and lagged impacts of ENSO events, TFP growth**

| | Tropical & humid countries | | | Arid & temperate countries | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\mathrm{ONI}_t \geq 0$ | -0.0178*** | -0.0162*** | -0.0207* | -0.0080 | -0.0063 | -0.0062 |
| | (0.0059) | (0.0059) | (0.0106) | (0.0075) | (0.0073) | (0.0073) |
| $\mathrm{ONI}_t < 0$ | -0.0096 | -0.0104* | -0.0138 | -0.0030 | -0.0018 | -0.0033 |
| | (0.0059) | (0.0058) | (0.0102) | (0.0081) | (0.0079) | (0.0076) |
| $\mathrm{SPEI}_t$ | | 0.0068*** | -0.0055 | | 0.0107*** | 0.0151** |
| | | (0.0022) | (0.0066) | | (0.0033) | (0.0059) |
| $\mathrm{ONI}_{t-1} \geq 0$ | | | -0.0168 | | | -0.0089 |
| | | | (0.0106) | | | (0.0072) |
| $\mathrm{ONI}_{t-1} < 0$ | | | -0.0014 | | | -0.0042 |
| | | | (0.0101) | | | (0.0073) |
| $\mathrm{ONI}_{t-1} \geq 0 \times SPEI_t$ | | | 0.0303** | | | 0.0063 |
| | | | (0.0121) | | | (0.0095) |
| $\mathrm{ONI}_{t-1} < 0 \times SPEI_t$ | | | 0.0222* | | | -0.0226** |
| | | | (0.0134) | | | (0.0114) |
| Constant | 0.0133 | 0.0121 | 0.0215 | 0.0057 | 0.0078 | 0.0109 |
| | (0.0122) | (0.0120) | (0.0176) | (0.0059) | (0.0060) | (0.0067) |
| Countries ($N$) | 30 | 30 | 30 | 30 | 30 | 30 |
| Observations ($N \times T$) | 1135 | 1135 | 1135 | 1058 | 1058 | 1058 |
| $R^2$ | 0.0463 | 0.0535 | 0.0460 | 0.0236 | 0.0359 | 0.0482 |
| PSAR(1) | Yes | Yes | Yes | Yes | Yes | Yes |

*Note: Prais-Winsten (PSCE) estimates. $ONI \geq 0$ and $ONI < 0$ stand respectively for El Niño and La Niña conditions. Standard errors are in parentheses. ***, **, and * indicate respectively 1%, 5%, and 10% significance levels. PSAR(1) stands for panel specific AR(1)-type autocorrelation.*

## 4. The influence of ENSO extreme events and weather patterns

In this section we provide further evidence for the robustness of our results when accounting for other climatic variables, ENSO extreme events and the possible influence of the duration of weather patterns.

*4.1. Disentangling the effects of temperature and precipitation*

Given that temperature and precipitation are the two critical variables implicated in defining the SPEI, it makes sense to examine robustness by replacing the SPEI by these two climatic variables in our regressions. Furthermore, disentangling the effects of temperature and precipitation may provide a better understanding of the role of weather patterns identified in the relationship between ENSO and economic growth.

We thus run separate regressions using temperature and precipitation data as climatic variables. We use monthly rainfall data (in $mm$) and monthly averages of mean daily temperatures at 2 meters height (in °C) from the Climate Research Unit (CRU). We extract these data from 1975 to 2014 for each grid point, and, as for the SPEI, we assign individual gridded data that falls in the croplands category of the GLC share to obtain weather data at the country level. However, the resulting average time series may be severely biased if countries' weather exhibit strong dispersion due to orographic and seasonal variations. To avoid this problem, we use standardized anomaly values rather than the raw values. This method provides a better measure of the year-to-year variability in precipitation and temperature at the country level.[31] Anomalies are measured as the deviation of weather data from their mean value calculated over the 1975-2014 period and then divided by their standard deviation measured over the same period as the mean. All calculations are made monthly, with the annual figures simply the average of the 12 monthly values. The resulting yearly time series of normalized precipitation and temperature anomalies are shown in Figures B.4 and B.4 in the Appendix.

Table 6 presents the results from specifications incorporating these two variables. In columns (1), (2), (4), and (5), the specification only includes temperature or precipitation. In contrast, in columns (3) and (6), we include both climatic variables to obtain unbiased estimates of their effects, given that they are historically correlated (Auffhammer et al., 2013).

Estimation results show that changing the weather variable does not affect our main results. For tropical and humid countries, the coefficient on the interaction term between El Niño and precipitation is significantly positive, confirming the idea that El Niño makes the growth pattern of this climate area more dependent on rainfall. The significant and negative coefficient on the interaction term with temperature provides further evidence of the negative growth effect of El Niño by causing unusual dry conditions in this climate area. Furthermore, including temperature and precipitation yields a significant negative growth effect of La Niña in arid and temperate countries transmitted by a rise in rainfall. This result also confirms the previously reported negative growth effect of La Niña in this climate area, where weather conditions become significantly

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[31]Deviations from climatology, defined as the long-term average of a given variable, are commonly used in the atmospheric sciences for understanding the relative importance of year-to-year variability and the longer-term changes caused by human activities.

wetter than usual. As a whole, these results suggest that the relationship between ENSO and growth caused by unusual dry and wet conditions highlighted in this paper is not driven by choice of weather variables. Finally, it is interesting to note that the use of the SPEI leads to more precise estimates of the coefficients on interaction terms, suggesting that the introduction of additional climatic variables altering the atmospheric demand for water provides a better understanding of the relationship between ENSO and economic growth.

Table 6: Contemporaneous and lagged impacts of ENSO events, temperature and precipitation

| | Tropical & humid countries | | | Arid & temperate countries | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $ONI_t \geq 0$ | -0.0154** | -0.0174*** | -0.0163*** | -0.0195** | -0.0228** | -0.0203** |
| | (0.00610) | (0.00581) | (0.00581) | (0.00863) | (0.00914) | (0.00870) |
| $ONI_t < 0$ | -0.00500 | -0.00682 | -0.00634 | -0.000604 | -0.00289 | -0.00174 |
| | (0.00593) | (0.00594) | (0.00589) | (0.00906) | (0.00985) | (0.00921) |
| $pre_t$ | -0.00118 | | -0.000717 | 0.00545* | | 0.00601* |
| | (0.00189) | | (0.00189) | (0.00296) | | (0.00316) |
| $tas_t$ | | 0.00355 | 0.00344 | | 0.00106 | 0.00243 |
| | | (0.00247) | (0.00249) | | (0.00293) | (0.00300) |
| $ONI_{t-1} \geq 0$ | -0.0118* | -0.0107* | -0.0118** | -0.0136 | -0.0151* | -0.0143* |
| | (0.00604) | (0.00574) | (0.00570) | (0.00849) | (0.00888) | (0.00853) |
| $ONI_{t-1} < 0$ | -0.00602 | -0.00473 | -0.00484 | -0.00632 | -0.00850 | -0.00665 |
| | (0.00569) | (0.00558) | (0.00553) | (0.00900) | (0.00939) | (0.00907) |
| $ONI_{t-1} \geq 0 \times pre_t$ | 0.0109*** | | 0.00893** | 0.00687 | | 0.00696 |
| | (0.00405) | | (0.00414) | (0.00517) | | (0.00553) |
| $ONI_{t-1} < 0 \times pre_t$ | 0.00298 | | 0.00217 | -0.0111* | | -0.0141** |
| | (0.00414) | | (0.00412) | (0.00609) | | (0.00654) |
| $ONI_{t-1} \geq 0 \times tas_t$ | | -0.0118** | -0.00998** | | -0.00352 | -0.00248 |
| | | (0.00482) | (0.00491) | | (0.00556) | (0.00564) |
| $ONI_{t-1} < 0 \times tas_t$ | | -0.00768 | -0.00743 | | -0.00648 | -0.0111* |
| | | (0.00484) | (0.00483) | | (0.00537) | (0.00569) |
| Constant | 0.0224* | 0.0223* | 0.0229* | 0.0260*** | 0.0282*** | 0.0268*** |
| | (0.0129) | (0.0131) | (0.0130) | (0.00824) | (0.00833) | (0.00784) |
| Countries ($N$) | 39 | 39 | 39 | 36 | 36 | 36 |
| Observations ($N \times T$) | 1521 | 1521 | 1521 | 1299 | 1299 | 1299 |
| $R^2$ | 0.0894 | 0.0884 | 0.0931 | 0.0803 | 0.0664 | 0.0891 |
| PSAR(1) | Yes | Yes | Yes | Yes | Yes | Yes |

*Note: Prais-Winsten (PSCE) estimates. $ONI \geq 0$ and $ONI < 0$ stand respectively for El Niño and La Niña conditions. "pre" and "tas" stand respectively for precipation and temperature normalized anomalies. Normalized temperature anomalies are expressed in first differences for tropical and humid countries due to the presence of a stochastic trend in the series. In contrast, they are expressed in level for arid and tropical countries. Normalized precipitation anomalies are stationary for both types of countries (see Table B.3 in the Appendix). Standard errors are in parentheses. \*\*\*, \*\*, and \* indicate respectively 1%, 5%, and 10% significance levels. PSAR(1) stands for panel specific AR(1)-type autocorrelation.*

*4.2. Accounting for ENSO extreme events*

As mentioned before, it is not clear whether the analysis of the asymmetric effects of the ENSO phases through the introduction of a Heaviside indicator fully captures the occurrence of extreme events. For example, years 1988 and 2010 show average values of ONI equal to -0.56°C and -0.19°C, respectively. Despite these low average negative values, these years are nevertheless characterized by the occurrence of La Niña events since during these two years ONI values lower than -1°C were observed during at least five consecutive months. By contrast, other years exhibit larger negative values of ONI but are characterized by neutral ENSO conditions due to the short duration of these anomalies. To address this issue, we use a specification that includes categorical variables − instead of a Heaviside indicator − to account more adequately for the different phases associated with ENSO (El Niño, La Niña or neutral phases):

$$\Delta y_{i,t} = \lambda + \alpha ENSO_t + \beta SPEI_{i,t} + \gamma ENSO_{t-1} + \delta\left(ENSO_{t-1} \times SPEI_{i,t}\right) + \mu_i + \varepsilon_{i,t} \tag{3}$$

where $ENSO_t$ is a categorical variable defined by annualized ONI anomalies in year $t$ such that:[32]

$$ENSO_t = \begin{cases} 1 & \text{if} \quad ONI < -1 \quad \text{during at least 5 months of the year t} \quad \text{(El Niño)} \\ 2 & \text{if} \quad ONI > 1 \quad \text{during at least 5 months of the year t} \quad \text{(La Niña)} \\ 0 & \text{otherwise} \quad \text{(Neutral)} \end{cases}$$

Neutral episodes are then the excluded episodes, so that the coefficients on La Niña and El Niño events must be interpreted differently than those in Equation (2). Indeed, the coefficients now measure the growth effect differential of La Niña and/or El Niño relative to neutral episodes, instead of analyzing the growth effects of ENSO according to the positive or the negative values taken by the variable ONI.

The estimation results of Equation (3) are reported in Table 7. We first notice that taking into account the duration and magnitude in the definition of ENSO does significantly change its estimated contemporaneous impact. Of particular importance is strong evidence of a more significant impact of El Niño in arid/temperate countries, suggesting a high sensibility of this climate zone to the intensities of this ENSO regime. Thus, compared to normal episodes, El Niño events seem to be now associated with lower growth rates in both climate areas. In contrast, and consistent with our previous results, La Niña events are not significantly different from normal ones for both climate areas. As can be seen, adding the delayed effects of ENSO on weather conditions does not significantly change the coefficient of the interaction term in tropical/humid

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[32]We have calculated the polychoric correlation coefficient between the ONI variable and dummy variables taking the value 1 in case of El Niño/La Niña events and 0 otherwise. The correlation between ONI and the dummy variable that captures El Niño is high (0.91) while the correlation with La Niña events is smaller (-0.76).

countries (column (3)). Indeed estimates for this climate area show similar results to previous ones. El Niño events are growth limiting by bringing unusual warmth in tropical/humid countries already experiencing dry conditions. Similarly, the use of this new measure of ENSO events confirms that La Niña, by causing increased rainfall, has a negative and lagged growth effect in arid/temperate areas with already wet conditions (column (6)). Overall, these findings support our main hypothesis related to the importance of local weather conditions when assessing the growth effects of ENSO cycles.

**Table 7: Contemporaneous and lagged impacts of ENSO events (dummy variables)**

|  | Tropical & humid countries | | | Arid & temperate countries | | |
|---|---|---|---|---|---|---|
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| El Niño$_t$ | -0.0068* | -0.0061 | -0.0080** | -0.0120** | -0.0139** | -0.0125*** |
|  | (0.0039) | (0.0038) | (0.0040) | (0.0053) | (0.0058) | (0.0048) |
| La Niña$_t$ | 0.0019 | 0.0015 | 0.0014 | 0.0055 | 0.0037 | 0.0060 |
|  | (0.0043) | (0.0042) | (0.0042) | (0.0056) | (0.0064) | (0.0051) |
| SPEI$_t$ |  | 0.0047** | 0.0001 |  | 0.0136*** | 0.0154*** |
|  |  | (0.0021) | (0.0030) |  | (0.0035) | (0.0045) |
| El Niño$_{t-1}$ |  |  | -0.0043 |  |  | -0.0065 |
|  |  |  | (0.0041) |  |  | (0.0052) |
| La Niña$_{t-1}$ |  |  | -0.0043 |  |  | -0.0059 |
|  |  |  | (0.0041) |  |  | (0.0050) |
| El Niño$_{t-1}$ ×SPEI$_t$ |  |  | 0.0117** |  |  | 0.0069 |
|  |  |  | (0.0049) |  |  | (0.0071) |
| La Niña$_{t-1}$ ×SPEI$_t$ |  |  | 0.0042 |  |  | -0.0175*** |
|  |  |  | (0.0053) |  |  | (0.0066) |
| Constant | 0.0141 | 0.0133 | 0.0162 | 0.0188*** | 0.0228*** | 0.0254*** |
|  | (0.0131) | (0.0129) | (0.0130) | (0.0047) | (0.0059) | (0.0050) |
| Countries ($N$) | 39 | 39 | 39 | 36 | 36 | 36 |
| Observations ($N \times T$) | 1521 | 1521 | 1521 | 1299 | 1299 | 1299 |
| $R^2$ | 0.0717 | 0.0742 | 0.0809 | 0.0744 | 0.0835 | 0.108 |
| PSAR(1) | Yes | Yes | Yes | Yes | Yes | Yes |

Note: Prais-Winsten (PSCE) estimates. Standard errors are in parentheses. ***, **, and * indicate respectively 1%, 5%, and 10% significance levels. PSAR(1) stands for panel specific AR(1)-type autocorrelation.

*4.3. Sensitivity to the duration of weather events*

We have used so far, as benchmark variable, the 6-month SPEI as it is usually considered as the most appropriate index when addressing events occurring at the agricultural season level (Vicente-Serrano et al., 2010, 2011). As demonstrated by McKee et al. (1993), water surplus/deficits can accumulate over time and impact differently usable water resources. Several studies have shown that the responses of soil moisture, river discharge, reservoir storage, vegetation activity and crop production can vary markedly as a function of the time scale (McKee et al., 1993; Vicente-Serrano et al., 2010; Beguería et al., 2014). It is then essential to control for the time scale over which weather conditions accumulate since the growth response to hydro-climatic conditions, and thus indirectly to ENSO events, can also vary as a function of time.[33]

Accordingly, we re-estimate Equations (2) and (3) using 3-month and 12-month SPEI. Using shorter time scales such as the 3-month SPEI can better reflect the impacts of ENSO on economic growth through short bursts of heavy rain or droughts. We also control for a longer time scale (12-month SPEI) since shorter extreme weather events may in some instances only be visible over a longer period, and thus not be necessarily detected over a 3-month period.[34] Tables 8 and 9 present the results of specifications (2) and (3) respectively incorporating these new values of SPEI.

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[33]Beside the time-scales over which weather patterns can be quantified, a number of studies have pointed out that the way economies adjust to hydro-meteorological conditions depends on the intensity of weather events (Burke et al., 2015). To address this issue, we have also estimated Equations (2) and (3) by adding a quadratic specification in the weather variable deemed to reflect extreme weather conditions. Results suggest no change in our main conclusions. For the sake of brevity, we do not report these results. They are available from the authors upon request.

[34]This happens, for example, when a short-term extreme event is bounded by relatively normal periods.

**Table 8: Accounting for the duration of weather conditions (heaviside variable)**

| | 12-month SPEI | | | | 3-month SPEI | | | |
|---|---|---|---|---|---|---|---|---|
| | Tropical & humid | | Arid & temperate | | Tropical & humid | | Arid & temperate | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\text{ONI}_t \geq 0$ | -0.0116** | -0.0160*** | -0.0157* | -0.0183** | -0.0121** | -0.0143*** | -0.0163* | -0.0197** |
| | (0.0054) | (0.0056) | (0.0084) | (0.0089) | (0.0059) | (0.0055) | (0.0086) | (0.0089) |
| $\text{ONI}_t < 0$ | -0.0035 | -0.0055 | 0.0028 | 0.0006 | -0.0026 | -0.0061 | 0.0036 | 0.0003 |
| | (0.0055) | (0.0055) | (0.0096) | (0.0095) | (0.0059) | (0.0054) | (0.0098) | (0.0094) |
| $\text{SPEI}_t$ | 0.0015 | -0.0048* | 0.0106*** | 0.0138*** | 0.0056** | 0.0018 | 0.0128*** | 0.0206*** |
| | (0.0017) | (0.0028) | (0.0028) | (0.0043) | (0.0027) | (0.0032) | (0.0043) | (0.0054) |
| $\text{ONI}_{t-1} \geq 0$ | | -0.0099* | | -0.0133 | | -0.0110** | | -0.0135 |
| | | (0.0056) | | (0.0090) | | (0.0055) | | (0.0090) |
| $\text{ONI}_{t-1} < 0$ | | -0.0081 | | -0.0067 | | -0.0070 | | -0.0076 |
| | | (0.0053) | | (0.0090) | | (0.0052) | | (0.0091) |
| $\text{ONI}_{t-1} \geq 0 \times SPEI_t$ | | 0.0146*** | | 0.0025 | | 0.0156** | | -0.0019 |
| | | (0.0052) | | (0.0085) | | (0.0075) | | (0.0096) |
| $\text{ONI}_{t-1} < 0 \times SPEI_t$ | | 0.0090* | | -0.0139* | | 0.0056 | | -0.0282** |
| | | (0.0054) | | (0.0075) | | (0.0078) | | (0.0119) |
| Constant | 0.0167 | 0.0227 | 0.0236*** | 0.0281*** | 0.0162 | 0.0221 | 0.0219*** | 0.0283*** |
| | (0.0165) | (0.0170) | (0.0071) | (0.0087) | (0.0163) | (0.0166) | (0.0068) | (0.0083) |
| Countries ($N$) | 39 | 39 | 36 | 36 | 39 | 39 | 36 | 36 |
| Observations ($N \times T$) | 1521 | 1521 | 1299 | 1299 | 1521 | 1521 | 1299 | 1299 |
| $R^2$ | 0.0960 | 0.1050 | 0.0736 | 0.0863 | 0.0986 | 0.1060 | 0.0687 | 0.0807 |
| PSAR(1) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Note: Prais-Winsten (PSCE) estimates. Standard errors are in parentheses. ***, **, and * indicate respectively 1%, 5%, and 10% significance levels. PSAR(1) stands for panel specific AR(1)-type autocorrelation.

**Table 9: Accounting for the duration of weather conditions (dummy variable)**

| | 12-month SPEI | | | | 3-month SPEI | | | |
|---|---|---|---|---|---|---|---|---|
| | Tropical & humid | | Arid & temperate | | Tropical & humid | | Arid & temperate | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| El Niño$_t$ | -0.0065* | -0.0085** | -0.0136** | -0.0161*** | -0.0062 | -0.0081** | -0.0117** | -0.0130*** |
| | (0.0039) | (0.0040) | (0.0058) | (0.0056) | (0.0038) | (0.0040) | (0.0053) | (0.0049) |
| La Niña$_t$ | 0.0017 | 0.0017 | 0.0035 | 0.0053 | 0.0013 | 0.0011 | 0.0059 | 0.0062 |
| | (0.0043) | (0.0043) | (0.0063) | (0.0061) | (0.0042) | (0.0042) | (0.0056) | (0.0052) |
| SPEI$_t$ | 0.0022 | -0.0024 | 0.0105*** | 0.0125*** | 0.0057** | 0.0013 | 0.0127*** | 0.0152*** |
| | (0.0018) | (0.0025) | (0.0028) | (0.0039) | (0.0026) | (0.0032) | (0.0039) | (0.0055) |
| El Niño$_{t-1}$ | | -0.0039 | | -0.0094 | | -0.0049 | | -0.0063 |
| | | (0.0041) | | (0.0061) | | (0.0041) | | (0.0052) |
| La Niña$_{t-1}$ | | -0.0042 | | -0.0046 | | -0.0041 | | -0.0056 |
| | | (0.0041) | | (0.0059) | | (0.0040) | | (0.0051) |
| El Niño$_{t-1}$ ×SPEI$_t$ | | 0.0120*** | | 0.0038 | | 0.0142** | | 0.0108 |
| | | (0.0038) | | (0.0063) | | (0.0060) | | (0.0095) |
| La Niña$_{t-1}$ ×SPEI$_t$ | | 0.0041 | | -0.0091* | | 0.0063 | | -0.0197** |
| | | (0.0045) | | (0.0055) | | (0.0064) | | (0.0084) |
| Constant | 0.0136 | 0.0158 | 0.0233*** | 0.0264*** | 0.0134 | 0.0166 | 0.0209*** | 0.0247*** |
| | (0.0130) | (0.0131) | (0.0062) | (0.0070) | (0.0129) | (0.0129) | (0.0047) | (0.0051) |
| Countries ($N$) | 39 | 39 | 36 | 36 | 39 | 39 | 36 | 36 |
| Observations ($N \times T$) | 1521 | 1521 | 1299 | 1299 | 1521 | 1521 | 1299 | 1299 |
| $R^2$ | 0.0725 | 0.0816 | 0.0813 | 0.0927 | 0.0741 | 0.0826 | 0.0879 | 0.102 |
| PSAR(1) | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Note: Prais-Winsten (PSCE) estimates. Standard errors are in parentheses. \*\*\*, \*\*, and \* indicate respectively 1%, 5%, and 10% significance levels. PSAR(1) stands for panel specific AR(1)-type autocorrelation.*

Several notable points emerge from these results. First, using the 3-month and 12-month SPEI does not change our results, providing further evidence for the robustness of our results and the importance of taking into account local weather conditions. However, the magnitude of this impact varies as a function of the time scale over which weather conditions accumulate. In particular, it is more pronounced at shorter time scales, i.e. for weather events that possibly begin and end rapidly. Using the 3-month SPEI leads to stronger adverse effects of La Niña, the year following its occurrence, in wet areas of the arid/temperate zone. Similarly, El Niño events are associated with a deeper delayed effect on the GDP growth of dry areas with a tropical/arid climate when considering shorter time scales, suggesting that the influence of ENSO on droughts is weakened at longer time scales in this climate area.

In order to illustrate how the growth effects of ENSO propagate throughout the time scale and for different hydrological conditions, we estimate its marginal growth effects at different levels and time-scales of SPEI. Figures 4 and 5 depict the marginal effect of ENSO phases at time $t-1$ on GDP growth as estimated from regressions (2) and (3) respectively.

As can be seen, in tropical and humid countries, the marginal growth effect of the El Niño variable is clearly different from zero at all negative SPEI (dry conditions) while for positive SPEI (wet conditions), it is close to zero. When wet conditions prevail, El Niño has no effect on growth, while at drier temperatures, by

inducing, with some delay, deficits in rainfall, it leads to significantly lower growth rates. The effect becomes weaker as the time scale of the SPEI gets progressively longer. In contrast, La Niña has no significant growth effects regardless of different SPEI values. These findings hold for both specifications using the Heaviside indicator or the dummy variable. For arid and temperate countries, the marginal growth effect of El Niño is not significant. However, the marginal growth effect of La Niña is significantly negative when wet conditions prevail (i.e. for positive values of the SPEI) and loses its significance as weather conditions become drier. This last finding confirms that La Niña, by bringing heavier precipitation in arid/temperate countries, leads to significantly lower growth when wet weather conditions prevail. Again this effect is less pronounced as the time scale of the SPEI gets progressively longer.

**Figure 4: Marginal effect of lagged ONI**

**(a) Tropical & humid countries**



**(b) Arid & temperate countries**
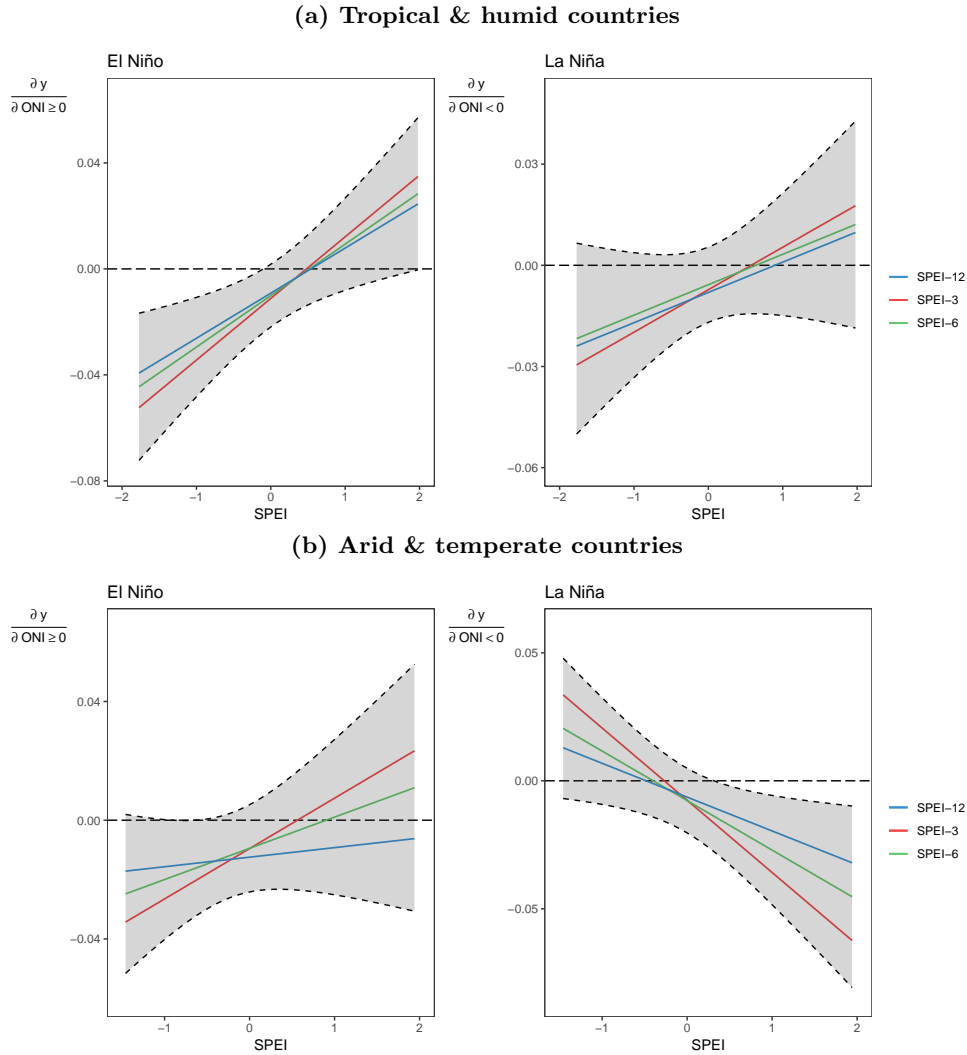


*Note: Solid lines report derivatives of the growth response with respect to changes in $ONI_{t-1}I(ONI_{t-1} \geq 0)$ (El Niño phases) and $ONI_{t-1}I(ONI_{t-1} < 0)$ (La Niña phases). Shaded areas represent 95% confidence intervals for the benchmark specification using the SPEI-6 month variable.*

**Figure 5: Marginal effects of lagged ENSO shocks**

**(a) Tropical & humid countries**
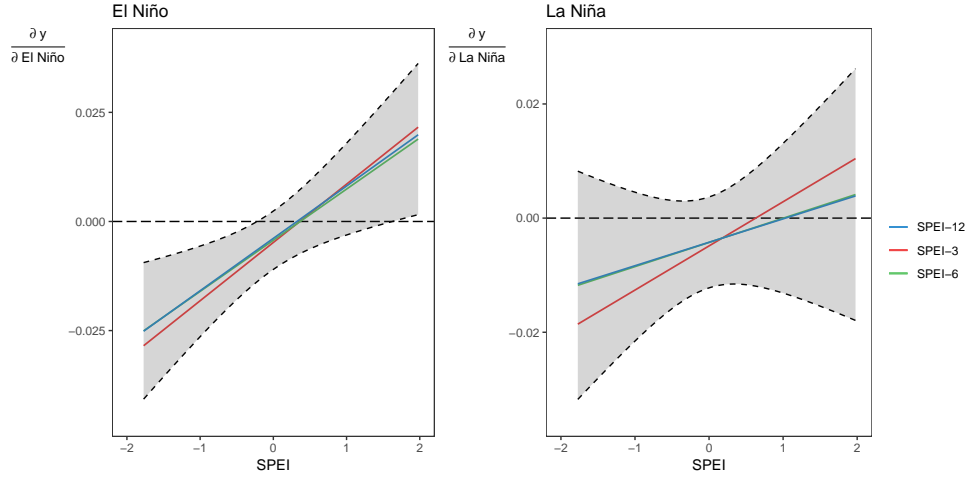


**(b) Arid & temperate countries**
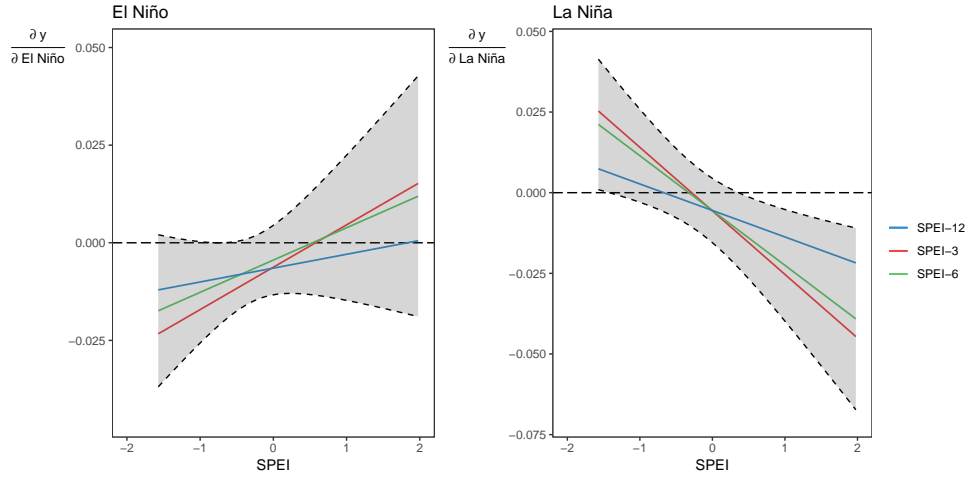


*Note: Solid lines report derivatives of the growth response with respect to discrete change from neutral regime to El Niño (La Niña) regime. Shaded areas represent 95% confidence intervals for the benchmark specification using the SPEI-6 month variable.*

## 5. Concluding remarks

In this paper, we investigated the economic consequences of ENSO events using a sample of 75 "teleconnected" countries over the period 1975-2014. We contributed to the existing literature in several respects. First, we analyzed the role of weather patterns in influencing the transmission of global climate cycles to economic growth. We addressed a number of empirical challenges that researchers face when studying the climate-growth nexus, by taking into account the heterogeneous and cumulative effects of weather patterns on economic activity. Second, we provided evidence for asymmetry and nonlinearity in the global influence of ENSO on economic growth by distinguishing weak from moderate to strong El Niño and La Niña events. Third, by also focusing on total factor productivity growth, our analysis shed some light on the long-lasting effects of ENSO events.

We showed that ENSO events have sizeable and delayed economic effects through their interactions with weather patterns in both tropical/humid and arid/temperate countries. In particular, El Niño regimes impact, with some delay, the GDP growth of dry areas in the tropical/humid zone by increasing their sensibility to wet conditions through a higher probability of drier than normal weather conditions. This lagged impact of El Niño on economic growth can be explained by its role in the occurrence of tropical droughts. In contrast, wet areas with an arid/temperate climate are found to be particularly vulnerable to La Niña events. Teleconnection patterns between La Niña and the weather in the arid/temperate zone favor higher than average precipitation that adversely affects economic growth in wet parts of this climate area. Moreover, we illustrated that there is a strong and monotonic relationship between the growth effects of ENSO and the time scales of weather patterns, this relationship being more pronounced over shorter time scales.

These findings are independent of the definition of weather variables, and how the asymmetric effects of ENSO are calculated. Indeed, these results hold if we select temperature and precipitation as climatic variables and if we consider two phases of the ENSO cycle − measured by positive (El Niño) or negative (La Niña) SSTs anomalies − or a neutral regime and two extreme regimes (El Niño or La Niña) defined according to their magnitude and duration. We also provided strong evidence that ENSO events affect total factor productivity growth through their interaction with weather patterns. This last finding has important implications. As productivity growth is reduced due to the delayed effects of ENSO on weather patterns, this fall is likely to have a negative impact on output growth in subsequent periods and possibly permanently alter income trajectories.

Overall, our results provide new evidence about the growth effects of both El Niño and La Niña, and suggest that a careful assessment of the complex linkages between climate shocks and growth is necessary. Indeed, studies focusing exclusively on the direct impacts of ENSO are likely to mask other essential dimen-

sions of climate variability, such as the asymmetry in hydro-meteorological responses (predominance of wet or humid conditions), or the duration of weather conditions which we showed had important consequences. Therefore, the relationship between ENSO events and economic growth is not only explained by the type of climate, but local weather conditions matter too.

In this respect, this paper, by analyzing the weather channel through which ENSO events impact economic growth, reproduced some of the stylized facts raised by the climate literature and in so doing, contributed to a better understanding of the causal mechanisms that underlie the variations in the growth effects of ENSO over time and across countries. By providing evidence for spatial heterogeneity, temporal diffusion and non-linearity in ENSO effects, our study can ultimately contribute to improve early warning systems against extreme weather and make adaptation more efficient, particularly in developing countries whose economies rely heavily on the agricultural sector. These concerns are becoming even more pressing since climate change is expected to further increase the strength of teleconnection patterns associated with ENSO events.

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# Appendix

*Appendix A: Data and statistical information*

## Table A.1: ENSO country assignment

| Country | ISO3 | Region | Climate | % of croplands | | |
|---|---|---|---|---|---|---|
| | | | | Trop. | Arid | Temp. |
| Albania | ALB | Europe & Central Asia | Arid & Temperate | 0.00 | 0.00 | 1.00 |
| Argentina | ARG | Latin America & Caribbean | Arid & Temperate | 0.00 | 0.02 | 0.98 |
| Armenia | ARM | Europe & Central Asia | Arid & Temperate | 0.00 | 0.33 | 0.67 |
| Australia | AUS | East Asia & Pacific | Arid & Temperate | 0.00 | 0.57 | 0.43 |
| Burundi | BDI | Sub-Saharan Africa | Tropical & Humid | 0.80 | 0.00 | 0.20 |
| Benin | BEN | Sub-Saharan Africa | Tropical & Humid | 0.75 | 0.25 | 0.00 |
| Burkina Faso | BFA | Sub-Saharan Africa | Arid & Temperate | 0.25 | 0.75 | 0.00 |
| Bangladesh | BGD | South Asia | Tropical & Humid | 0.87 | 0.00 | 0.13 |
| Bulgaria | BGR | Europe & Central Asia | Tropical & Humid | 0.00 | 0.00 | 1.00 |
| Belarus | BLR | Europe & Central Asia | Arid & Temperate | 0.00 | 0.00 | 1.00 |
| Belize | BLZ | Latin America & Caribbean | Tropical & Humid | 1.00 | 0.00 | 0.00 |
| Bolivia | BOL | Latin America & Caribbean | Tropical & Humid | 0.82 | 0.12 | 0.05 |
| Brazil | BRA | Latin America & Caribbean | Tropical & Humid | 0.75 | 0.10 | 0.16 |
| Botswana | BWA | Sub-Saharan Africa | Arid & Temperate | 0.00 | 1.00 | 0.00 |
| Chile | CHL | Latin America & Caribbean | Arid & Temperate | 0.00 | 0.01 | 0.99 |
| China | CHN | East Asia & Pacific | Arid & Temperate | 0.00 | 0.32 | 0.68 |
| Cameroon | CMR | Sub-Saharan Africa | Tropical & Humid | 0.67 | 0.33 | 0.00 |
| Congo, Democratic Republic | COD | Sub-Saharan Africa | Tropical & Humid | 0.95 | 0.00 | 0.05 |
| Congo | COG | Sub-Saharan Africa | Tropical & Humid | 1.00 | 0.00 | 0.00 |
| Colombia | COL | Latin America & Caribbean | Tropical & Humid | 0.85 | 0.00 | 0.15 |
| Costa Rica | CRI | Latin America & Caribbean | Tropical & Humid | 0.99 | 0.00 | 0.01 |
| Cyprus | CYP | Europe & Central Asia | Arid & Temperate | 0.00 | 0.52 | 0.48 |
| Dominican Republic | DOM | Latin America & Caribbean | Tropical & Humid | 0.97 | 0.00 | 0.03 |
| Algeria | DZA | Middle East & North Africa | Arid & Temperate | 0.00 | 0.31 | 0.69 |
| Ecuador | ECU | Latin America & Caribbean | Tropical & Humid | 0.73 | 0.07 | 0.20 |
| Egypt | EGY | Middle East & North Africa | Arid & Temperate | 0.00 | 1.00 | 0.00 |
| Gabon | GAB | Sub-Saharan Africa | Tropical & Humid | 1.00 | 0.00 | 0.00 |
| Gambia | GMB | Sub-Saharan Africa | Arid & Temperate | 0.10 | 0.90 | 0.00 |
| Greece | GRC | Europe & Central Asia | Arid & Temperate | 0.00 | 0.11 | 0.89 |
| Guatemala | GTM | Latin America & Caribbean | Tropical & Humid | 0.85 | 0.00 | 0.15 |
| Honduras | HND | Latin America & Caribbean | Tropical & Humid | 0.90 | 0.00 | 0.10 |
| Indonesia | IDN | East Asia & Pacific | Tropical & Humid | 1.00 | 0.00 | 0.00 |
| India | IND | South Asia | Tropical & Humid | 0.36 | 0.36 | 0.28 |
| Iran | IRN | Middle East & North Africa | Arid & Temperate | 0.00 | 0.61 | 0.39 |
| Kenya | KEN | Sub-Saharan Africa | Tropical & Humid | 0.57 | 0.20 | 0.23 |
| Cambodia | KHM | East Asia & Pacific | Tropical & Humid | 1.00 | 0.00 | 0.00 |
| Lao People's Democratic Republic | LAO | East Asia & Pacific | Tropical & Humid | 0.87 | 0.00 | 0.13 |
| Sri Lanka | LKA | South Asia | Tropical & Humid | 1.00 | 0.00 | 0.00 |
| Lesotho | LSO | Sub-Saharan Africa | Arid & Temperate | 0.00 | 0.00 | 1.00 |
| Morocco | MAR | Middle East & North Africa | Arid & Temperate | 0.00 | 0.33 | 0.67 |
| Moldova, Republic of | MDA | Europe & Central Asia | Arid & Temperate | 0.00 | 0.00 | 1.00 |
| Madagascar | MDG | Sub-Saharan Africa | Tropical & Humid | 0.82 | 0.00 | 0.18 |
| Mexico | MEX | Latin America & Caribbean | Tropical & Humid | 0.70 | 0.10 | 0.20 |
| Mali | MLI | Sub-Saharan Africa | Arid & Temperate | 0.20 | 0.80 | 0.00 |
| Mozambique | MOZ | Sub-Saharan Africa | Arid & Temperate | 0.33 | 0.57 | 0.10 |
| Mauritania | MRT | Sub-Saharan Africa | Arid & Temperate | 0.00 | 1.00 | 0.00 |

| Country | Code | Region | Climate | | | |
|---|---|---|---|---|---|---|
| Mauritius | MUS | Sub-Saharan Africa | Tropical & Humid | 1.00 | 0.00 | 0.00 |
| Malaysia | MYS | East Asia & Pacific | Tropical & Humid | 1.00 | 0.00 | 0.00 |
| Namibia | NAM | Sub-Saharan Africa | Arid & Temperate | 0.00 | 1.00 | 0.00 |
| Nigeria | NGA | Sub-Saharan Africa | Tropical & Humid | 0.72 | 0.28 | 0.00 |
| New Zealand | NZL | East Asia & Pacific | Arid & Temperate | 0.00 | 0.00 | 1.00 |
| Pakistan | PAK | South Asia | Arid & Temperate | 0.00 | 0.83 | 0.17 |
| Peru | PER | Latin America & Caribbean | Tropical & Humid | 0.48 | 0.24 | 0.28 |
| Philippines | PHL | East Asia & Pacific | Tropical & Humid | 0.99 | 0.00 | 0.01 |
| Paraguay | PRY | Latin America & Caribbean | Arid & Temperate | 0.34 | 0.07 | 0.59 |
| Romania | ROU | Europe & Central Asia | Arid & Temperate | 0.00 | 0.00 | 1.00 |
| Russian Federation | RUS | Europe & Central Asia | Arid & Temperate | 0.00 | 0.19 | 0.81 |
| Sudan | SDN | Sub-Saharan Africa | Arid & Temperate | 0.07 | 0.93 | 0.00 |
| Senegal | SEN | Sub-Saharan Africa | Arid & Temperate | 0.02 | 0.98 | 0.00 |
| Sierra Leone | SLE | Sub-Saharan Africa | Tropical & Humid | 1.00 | 0.00 | 0.00 |
| El Salvador | SLV | Latin America & Caribbean | Tropical & Humid | 1.00 | 0.00 | 0.00 |
| Serbia | SRB | Europe & Central Asia | Arid & Temperate | 0.00 | 0.00 | 1.00 |
| Swaziland | SWZ | Sub-Saharan Africa | Tropical & Humid | 1.00 | 0.00 | 0.00 |
| Togo | TGO | Sub-Saharan Africa | Tropical & Humid | 1.00 | 0.00 | 0.00 |
| Thailand | THA | East Asia & Pacific | Tropical & Humid | 1.00 | 0.00 | 0.00 |
| Tajikistan | TJK | Europe & Central Asia | Arid & Temperate | 0.00 | 0.68 | 0.32 |
| Tunisia | TUN | Middle East & North Africa | Arid & Temperate | 0.00 | 0.04 | 0.96 |
| Turkey | TUR | Middle East & North Africa | Arid & Temperate | 0.00 | 0.09 | 0.91 |
| Tanzania | TZA | Sub-Saharan Africa | Tropical & Humid | 0.72 | 0.20 | 0.08 |
| Uganda | UGA | Sub-Saharan Africa | Tropical & Humid | 0.94 | 0.04 | 0.02 |
| Ukraine | UKR | Europe & Central Asia | Arid & Temperate | 0.00 | 0.00 | 1.00 |
| Uruguay | URY | Latin America & Caribbean | Arid & Temperate | 0.00 | 0.00 | 1.00 |
| Venezuela, Bolivarian Republic of | VEN | Latin America & Caribbean | Tropical & Humid | 1.00 | 0.00 | 0.00 |
| Vietnam | VNM | East Asia & Pacific | Tropical & Humid | 0.67 | 0.00 | 0.33 |
| South Africa | ZAF | Sub-Saharan Africa | Arid & Temperate | 0.02 | 0.58 | 0.40 |

**Table A.2: Correlation coefficients between ONI, the Niño 3.4 index and SOI**

|                | ONI    | SOI    | Niño 3.4 index |
|----------------|--------|--------|----------------|
| ONI            | 1.000  |        |                |
| SOI            | -0.924 | 1.000  |                |
| Niño 3.4 index | 0.981  | -0.882 | 1.000          |

*Note: The Niño 3.4 index uses the same region as ONI, but is based on a 5-month running mean. The Equatorial Southern Oscillation Index (SOI) is a standardized index based on the observed sea level pressure differences between eastern equatorial Pacific and Indonesia.*

**Figure A.2: Evolution of the main ENSO indices (1975-2014)**

ONI (black), Niño 3.4 (blue) & SOI (red)
3–Month Average
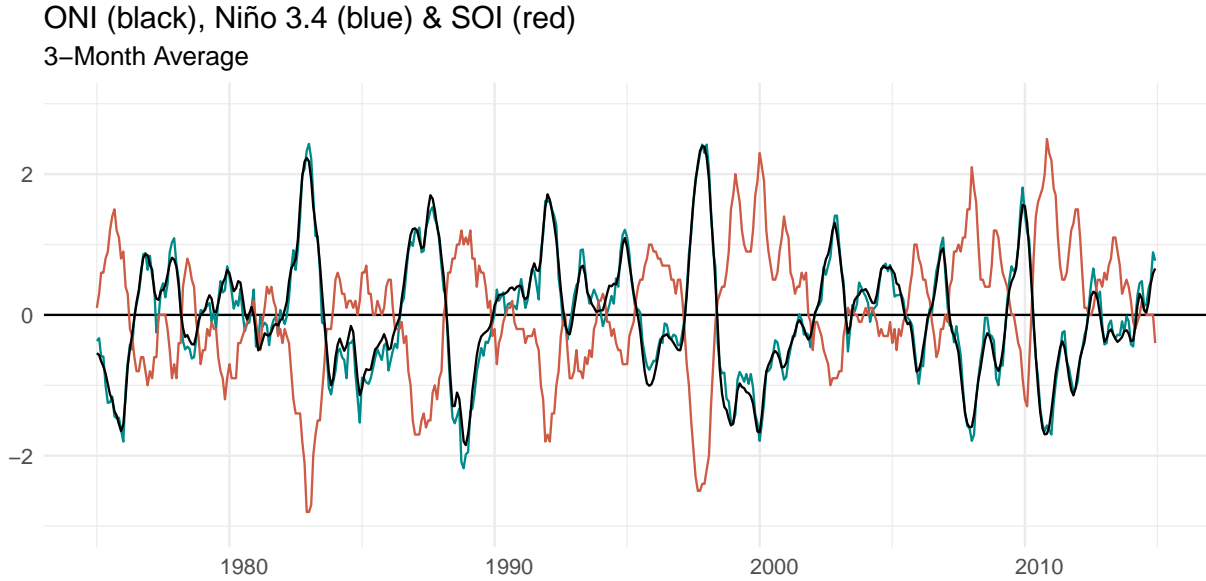


**Table A.3: Variables and data sources**

| Mnemonic | Source                   | Variable description                                    |
|----------|--------------------------|---------------------------------------------------------|
| $ONI$    | NOAA database            | Oceanic Niño Index                                      |
| $SPEI$   | Climate Research Unit    | Standardised Precipitation-Evapotranspiration Index     |
| $tas$    | Climate Research Unit    | Monthly averages of daily surface temperatures          |
| $pre$    | Climate Research Unit    | Total monthly precipitation                             |
| $y$      | Penn World Table database | Real GDP per capita (in 2011 US dollars)               |
| $TFP$    | Penn World Table database | Real Total Factor Productivity per capita (Index 2011=1, Annual) |

*Appendix B: Computation of weather series*

*B.1: The SPEI*

The Standardized Precipitation and Evapotranspiration Index (SPEI) developed by Vicente-Serrano et al. (2010) is calculated, for a month $i$, as the difference ($D_i$) between precipitation ($P_i$) and potential evapotranspiration ($PET$):

$$D_i = P_i - PET_i \tag{4}$$

Where $PET_i$ is monthly averages of daily potential evapotranspiration estimates (in $mm/day$). Potential evapotranspiration represents the idealized quantity of water evaporated per $-$ unit area, per unit time under existing atmospheric conditions. We use the following updated Penman-Monteith equation recommended by the FAO (FAO-56 Penman-Monteith):[35]

$$PET_i = \frac{0.408\Delta \left( R_n - G \right) + \gamma \frac{900}{T+273} u_2 \left( e_s - e_a \right)}{\Delta + \gamma \left( 1 + 0.34 u_2 \right)} \tag{5}$$

where,

$R_n$: net radiation at the crop surface (MJ m$^{-2}$ day$^{-1}$),
$G$: soil heat flux density (MJ m$^{-2}$ day$^{-1}$),
$T$: mean daily air surface temperature at 2m height (°C),
$u_2$: wind speed at 2m height ($m/s$),
$e_s$: saturation vapour pressure (kPa),
$e_a$: actual vapour pressure (kPa),
$D$: slope vapour pressure curve (kPa °C$^{-1}$),
$\gamma$: psychrometric constant (kPa °C$^{-1}$).

The $D_i$ series then reflect the water surplus or deficit for the current month. The calculated $D_i$ values are then aggregated at various time scales $k$ (3, 6 and 12 months). The aggregated water surplus or deficits values ($D_n^k$) are obtained by the sum of the $D_i$ values from $k-1$ months before the $n^{th}$ current month:

$$D_n^k = \sum_{l=0}^{k-1} (P_{n-l} - PET_{n-l}) \text{ with } n \geq k \tag{6}$$

Given the strong differences in climatic regimes within and between countries, the $D_n^k$ series are fitted

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[35]Standardized indicators such as the SPEI are sensitive to the method of calculation of the potential evapotranspiration ($PET$). We use a PET estimate based on the Penman-Monteith equation of water balance rather than the Thornthwaite method since Penman-type approach is considered to be more physically realistic.

to a probability distribution to transform the original values to standardized units that are comparable in space and time and at different time scales. A density function of log-logistic probability is adjusted to the distribution of the variable $D_n^k$ since it allows a better behavior of the SPEI to extreme events. The probability density function of a three parameter Log-logistic distributed variable is expressed as:

$$f(x) = \frac{\omega}{\theta} \left( \frac{x - \mu}{\vartheta} \right)^{\omega - 1} \left( 1 + \left( \frac{x - \mu}{\vartheta} \right)^{\omega} \right)^{-2} \tag{7}$$

where $\theta$, $\omega$ and $\mu$ are parameters of scale, shape and origin for $D_n^k$ values in the range ($\mu > D < \infty$). The parameters are estimated using the L-moments procedure. $f(x)$ is transformed into a random variable with mean zero and a variance equals to one. Thus, the value of the SPEI is bounded between -3 and 3. Between these two values, different intensities in hydro-climatic conditions can be identified, according threshold values reached by the SPEI, as shown in Table *B.1*.

**Table B.1: Hydro-climatic conditions according to threshold values of the SPEI**

| Values of SPEI | Hydro-climatic conditions |
|---|---|
| $SPEI > 2$ | Exceptionally moist |
| $1.60 < SPEI < 1.99$ | Extremely moist |
| $1.30 < SPEI < 1.59$ | Very moist |
| $0.80 < SPEI < 1.29$ | Moderately moist |
| $0.51 < SPEI < 0.79$ | Slightly moist |
| $-0.50 < SPEI < 0.50$ | Near normal conditions |
| $-0.79 < SPEI < -0.51$ | Slightly dry |
| $-1.29 < SPEI < -0.80$ | Moderately dry |
| $-1.59 < SPEI < -1.30$ | Very dry |
| $-1.99 < SPEI < -1.60$ | Extremely dry |
| $SPEI < -2$ | Exceptionally dry |

*Source: NOAA's National Centers for Environmental Information, 2015.*

*B.2: Deriving the average SPEI by country*

Annual SPEI values are obtained by averaging the twelve monthly SPEI of each year included in the period 1975-2014. However, as these values are calculated for every single grid cell, they must be aggregated to the country level to fit the purpose of our paper. We then calculate country-level indicators by taking the average of SPEI across grid cells that overlap a country's cropland areas. In this way, we are able to average weather observations over land covers which are relevant for agriculture and share broadly the same climate, for each country. The cropland areas are defined according to the Global Land Cover SHARE (GLC-SHARE)

classification.[36] We illustrate the advantages of this averaging method by taking the example of Mali in 2010. As can be seen in Figure B.1, Mali is a typical example of a country largely dominated by drylands where little economic activity and sparse populations dominate. Aggregating climate data at the country level without excluding these areas could bias the measurement of climate effects on economic growth and thus fail to accurately identify ENSO impacts channeled through weather conditions prevailing in cropland areas.

**Figure B.1: Land covers distribution, Mali (2010)**
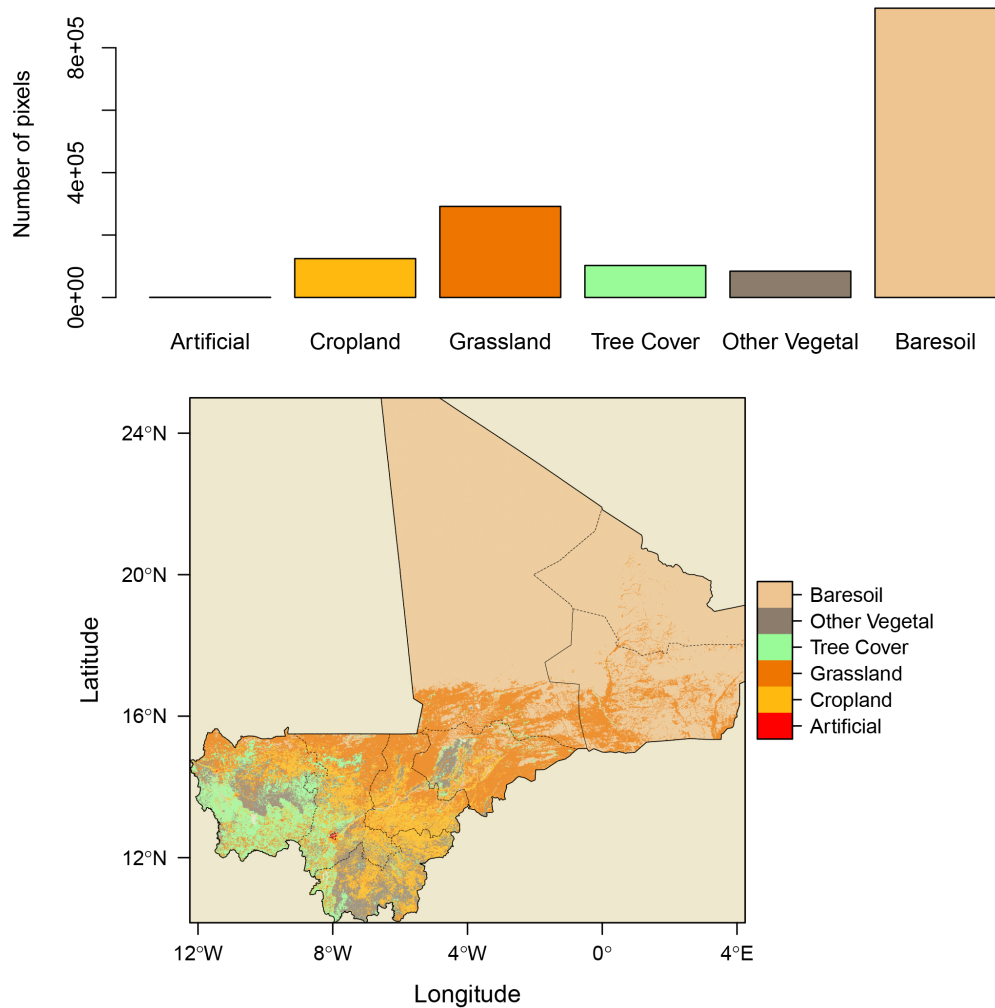


*Note: Land covers types are those defined by the GLC-SHARE. For the sake of readability, the category Other Vegetal regroups the following LCCS: shrubs covered areas (05), herbaceous vegetation, aquatic or regularly flooded (06), mangroves (07) and sparse vegetation (08).*

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[36]This Global Land Cover database, developed by the Land and Water Division of Food and Agriculture Organisation (FAO), has a spatial resolution of 30 arc-seconds. This database compiles previously scattered and unharmonized land cover information from around the globe into one centralized database. Eleven land covers types are then aggregated following the Land Cover Classification System (LCCS): artificial surfaces (01), cropland (02), grassland (03), tree covered areas (04), shrubs covered areas (05), herbaceous vegetation, aquatic or regularly flooded (06), mangroves (07), sparse vegetation (08), bare soil (09), snow and glaciers (10), and water bodies (11).

Indeed, as shown in Figure B.2, the shape of the SPEI distribution in Mali in 2010 differed considerably depending on the type of land cover. Although 18.2% of the territory was affected by drier conditions during 2010, the desert areas located in the north of the country were the most challenged by drought. On the contrary, the rest of the country − and particularly croplands − was characterized by wetter conditions. This high spatial variability is therefore likely to smooth out the impact of extreme meteorological conditions during the spatial aggregation process. By contrast, averaging SPEI across grid cells that overlap only cropland areas leads to a value of the SPEI more consistent with weather-related risks in agriculture.

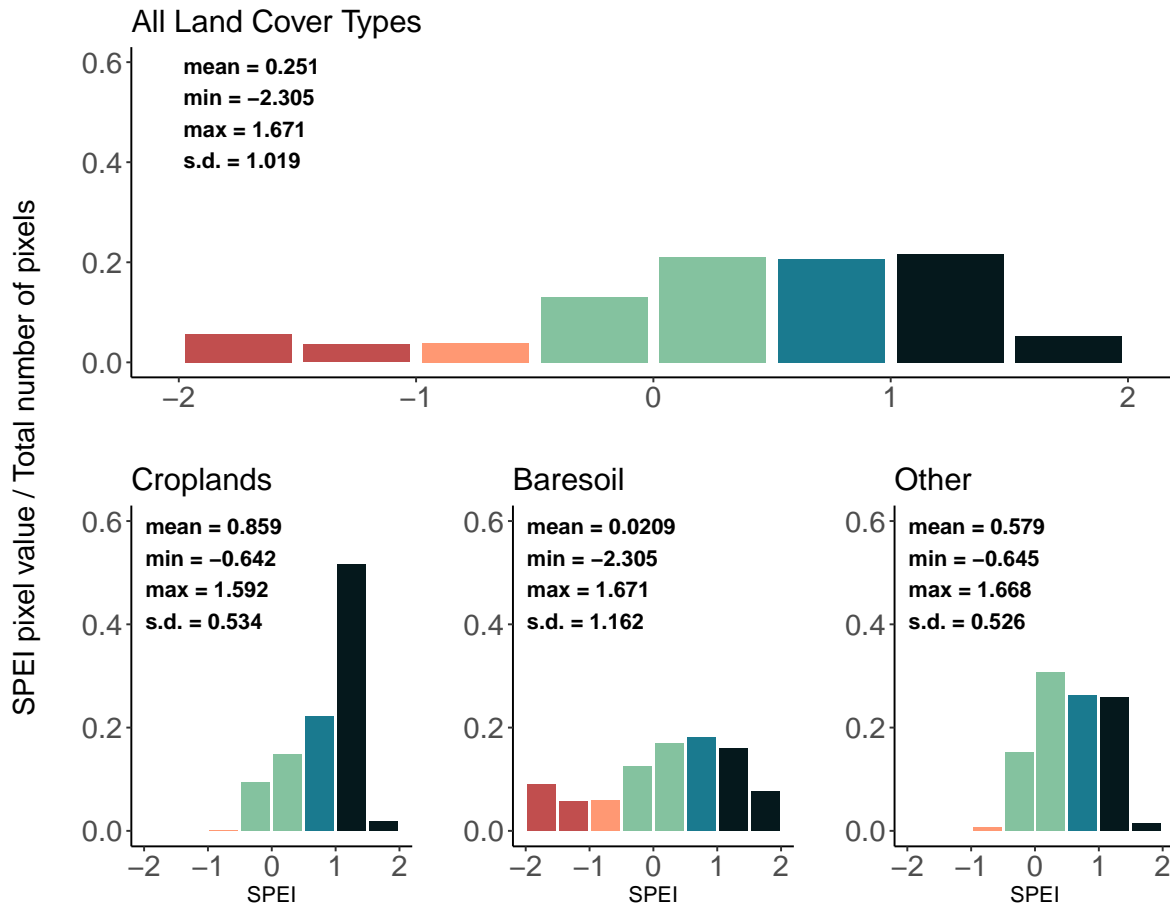**Figure B.2: SPEI distribution and land cover types, Mali (2010)**

Figure B.3: 6-month SPEI times series

6-month SPEI

year

Figure B.4: Normalized anomalies of air temperature times series

year

tas

Figure B.5: Normalized anomalies of precipitation times series

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*Appendix C: Data analysis*

**Table C.1: Test for residual**

| | Tropical & humid countries | | Arid & temperate countries | |
|---|---|---|---|---|
| | FE | RE | FE | RE |
| ONI$_t \geq 0$ | -0.0228*** | -0.0228*** | -0.0204*** | -0.0204*** |
| | (0.0042) | (0.0042) | (0.0059) | (0.0059) |
| | [0.0044] | [0.0043] | [0.0067] | [0.0067] |
| ONI$_t < 0$ | -0.0080** | -0.0081** | 0.0007 | 0.0006 |
| | (0.0040) | (0.0040) | (0.0055) | (0.0055) |
| | [0.0034] | [0.0034] | [0.0040] | [0.0040] |
| SPEI$_t$ | -0.0040 | -0.0040 | 0.0168*** | 0.0152*** |
| | (0.0040) | (0.0040) | (0.0056) | (0.0055) |
| | [0.0038] | [0.0038] | [0.0044] | [0.0040] |
| ONI$_{t-1} \geq 0$ | -0.0148*** | -0.0148*** | -0.0150** | -0.0148** |
| | (0.0042) | (0.0042) | (0.0059) | (0.0059) |
| | [0.0047] | [0.0047] | [0.0056] | [0.0056] |
| ONI$_{t-1} < 0$ | -0.0073* | -0.0073* | -0.0068 | -0.0065 |
| | (0.0039) | (0.0039) | (0.0054) | (0.0054) |
| | [0.0050] | [0.0050] | [0.0050] | [0.0051] |
| ONI$_{t-1} \geq 0 \times SPEI_t$ | 0.0173** | 0.0172** | 0.0092 | 0.0099 |
| | (0.0077) | (0.0077) | (0.0105) | (0.0105) |
| | [0.0091] | [0.0092] | [0.0093] | [0.0098] |
| ONI$_{t-1} < 0 \times SPEI_t$ | 0.0126 | 0.0129 | -0.0226** | -0.0207** |
| | (0.0079) | (0.0079) | (0.0098) | (0.0097) |
| | [0.0061] | [0.0059] | [0.0071] | [0.0068] |
| Constant | 0.0291*** | 0.0291*** | 0.0271*** | 0.0262*** |
| | (0.0027) | (0.0036) | (0.0036) | (0.0042) |
| | [0.0029] | [0.0034] | [0.0031] | [0.0040] |
| Pesaran CSD | 13.881*** | | 11.433*** | |
| Autocorrelation Test | 31.809*** | | 9.384*** | |
| Modified Wald Test | 1650.50*** | | 4657.73*** | |
| Sargan-Hansen Stat. | 41.245*** | | 11.652** | |
| Observations | 1521 | | 1299 | |
| Countries | 39 | | 36 | |
| $R^2$ | 0.0330 | | 0.0462 | |

*Note: FE stands for fixed effect model and RE for random effect model. Standard errors are in parentheses and robust standard errors are in brackets. \*\*\*, \*\*, and \* indicate respectively 1%, 5%, and 10% significance levels.*

## Table C.2: Pesaran CD test for cross-section independence

| Variable | CD-test | Correlation | abs(correlation) |
|---|---|---|---|
| $\Delta y$ | 32.52*** | 0.100 | 0.189 |
| $\Delta TFP$ | 18.84*** | 0.074 | 0.176 |
| $SPEI$ | 16.91*** | 0.049 | 0.190 |

*Note: The CD test of Pesaran (2004) is defined under the null hypothesis of no cross-sectional dependence. ***, **, and * indicate 1%, 5%, and 10% significance levels.*

## Table C.3: Cross-sectionally augmented Im, Pesaran and Shin (IPS) test for unit roots

| | | Tropical & humid countries | | | | Arid & temperate countries | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Without Trend $\bar{Z}_t$ | | With Trend $\bar{Z}_t$ | | Without Trend $\bar{Z}_t$ | | With Trend $\bar{Z}_t$ | |
| Variable | lags | Level | 1st Diff | Level | 1st Diff | Level | 1st Diff | Level | 1st Diff |
| $y$ | 0 | -0.578 | -15.846 | 0.430 | -14.983*** | 0.030 | -15.461*** | 1.630 | -14.808*** |
| | 1 | -1.762** | -11.437 | -2.284** | -10.391*** | -2.542*** | -11.344*** | -1.301* | -10.311*** |
| | 2 | -0.108 | -6.852 | -0.173 | -4.874*** | -1.290 | -6.931*** | 0.620 | -5.341*** |
| | 3 | 0.943 | -6.59 | 0.607 | -4.312*** | -0.048 | -4.735*** | 1.350 | -2.539*** |
| $TFP$ | 0 | 0.406 | -18.296 | -0.085 | -16.565*** | 0.390 | -18.029*** | -0.604 | -16.98*** |
| | 1 | -0.631 | -13.157 | -2.831*** | -10.756*** | -0.524 | -13.444*** | -2.222** | -11.723*** |
| | 2 | 0.663 | -8.043 | -0.917 | -4.902*** | 1.005 | -8.605*** | -0.673 | -6.604*** |
| | 3 | 0.891 | -7.196 | -0.434 | -3.777*** | 1.879 | -5.229*** | 0.580 | -2.316*** |
| $SPEI$ | 0 | -19.646*** | . | -18.088*** | . | -17.899*** | . | -16.768*** | . |
| | 1 | -12.829*** | . | -11.257*** | . | -11.591*** | . | -10.101*** | . |
| | 2 | -8.697*** | . | -7.138*** | . | -8.097*** | . | -6.620*** | . |
| | 3 | -7.377*** | . | -6.139*** | . | -5.148*** | . | -3.464*** | . |
| $pre$ | 0 | -22.348*** | . | -21.065*** | . | -20.715*** | . | -20.789*** | . |
| | 1 | -13.507*** | . | -11.983*** | . | -11.903*** | . | -11.619*** | . |
| | 2 | -10.413*** | . | -9.259*** | . | -7.179*** | . | -6.783*** | . |
| | 3 | -8.018*** | . | -6.705*** | . | -4.259*** | . | -3.419*** | . |
| $tas$ | 0 | -14.844*** | . | -12.416*** | -25,189*** | -18.670*** | . | -17.204*** | . |
| | 1 | -7.284*** | . | -1.669* | -20,872*** | -12.142*** | . | -9.872*** | . |
| | 2 | -4.547*** | . | -1.034 | -11,092*** | -10.204*** | . | -8.274*** | . |
| | 3 | -3.569*** | . | -0.191 | -7,574*** | -9.568*** | . | -6.994*** | . |

*Note: ***, **, and * denote the rejection of the null hypothesis at the 10%, 5% and 1% level. The null hypothesis is the presence of unit root in panel data with cross-sectional dependence in the form of common factor dependence.*

**Table C.4: Results from System-GMM estimates, Heaviside variable**

| | Tropical & humid countries | | | Arid & temperate countries | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\Delta y_{t-1}$ | 0.366*** | 0.361*** | 0.355*** | 0.336*** | 0.343*** | 0.353*** |
| | (0.0619) | (0.0619) | (0.0606) | (0.0745) | (0.0705) | (0.0695) |
| $\mathrm{ONI}_t \geq 0$ | -0.0094** | -0.0085* | -0.0099** | -0.0164** | -0.0136** | -0.0146** |
| | (0.0045) | (0.0046) | (0.0043) | (0.0065) | (0.0063) | (0.0058) |
| $\mathrm{ONI}_t < 0$ | -0.0014 | -0.0018 | -0.0022 | 0.0000 | 0.0020 | 0.0002 |
| | (0.0033) | (0.0033) | (0.0029) | (0.0042) | (0.0044) | (0.0039) |
| $\mathrm{SPEI}_t$ | | 0.0042** | -0.0035 | | 0.0135*** | 0.0227*** |
| | | (0.0020) | (0.0028) | | (0.0040) | (0.0064) |
| $\mathrm{ONI}_{t-1} \geq 0$ | | | -0.0036 | | | -0.0064 |
| | | | (0.0050) | | | (0.0051) |
| $\mathrm{ONI}_{t-1} < 0$ | | | -0.0059 | | | -0.0129*** |
| | | | (0.0050) | | | (0.0045) |
| $\mathrm{ONI}_{t-1} \geq 0 \times SPEI_t$ | | | 0.0206** | | | -0.0064 |
| | | | (0.0089) | | | (0.0095) |
| $\mathrm{ONI}_{t-1} < 0 \times SPEI_t$ | | | 0.0080* | | | -0.0347*** |
| | | | (0.0047) | | | (0.0102) |
| Constant | 0.0128*** | 0.0128*** | 0.0156*** | 0.0148*** | 0.0146*** | 0.0190*** |
| | (0.0019) | (0.0020) | (0.0037) | (0.0030) | (0.0031) | (0.0035) |
| Observations ($N \times T$) | 1482 | 1482 | 1482 | 1263 | 1263 | 1263 |
| $\chi^2$ | 75.61*** | 83.47*** | 108.2*** | 36.20*** | 71.32*** | 157.3*** |
| Tests of over-identification restrictions | | | | | | |
| Sargan test: $\chi^2(36)$ | 86.70*** | 85.28*** | 87.77*** | 109.4*** | 109.9*** | 106.4*** |
| Hansen test: $\chi^2(36)$ | 35.15 | 34.90 | 33.32 | 33.95 | 35.01 | 30.84 |
| Arellano-Bond test for AR(1) in first differences | | | | | | |
| $z$ | -4.624 | -4.621 | -4.600 | -3.901 | -3.956 | -3.961 |
| $Pr > z$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Arellano-Bond test for AR(2) in first differences | | | | | | |
| $z$ | -0.469 | -0.396 | -0.370 | 0.622 | 0.586 | 0.459 |
| $Pr > z$ | 0.639 | 0.692 | 0.712 | 0.534 | 0.558 | 0.646 |

*Note: ***, **, and * denote the rejection of the null hypothesis at the 10%, 5% and 1% level. Robust standard errors are in parentheses. We restrict the maximum lag length of the lagged instruments to one lag. Results are insensitive to the choice of alternative maximum lag lengths. Results using up to four lags are available upon request.*

**Table C.5: Placebo test**

| | Tropical & humid countries | | | | Arid & temperate countries | |
| --- | --- | --- | --- | --- | --- | --- |
| | PCSE | | DK | | PCSE | DK |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $ONI_t \geq 0$ | -0.0186*** | -0.0187*** | -0.0228*** | -0.0228*** | -0.0181* | -0.0208* |
| | (0.00579) | (0.00578) | (0.00673) | (0.00680) | (0.00946) | (0.0108) |
| $ONI_t < 0$ | -0.00871 | -0.00867 | -0.0102 | -0.0101 | -0.000509 | -0.00432 |
| | (0.00550) | (0.00549) | (0.00673) | (0.00675) | (0.00971) | (0.00988) |
| $SPEI_t$ | -0.00195 | -0.00210 | -0.00449 | -0.00469 | 0.0177*** | 0.0163** |
| | (0.00358) | (0.00365) | (0.00465) | (0.00467) | (0.00648) | (0.00629) |
| $ONI_{t-1} \geq 0$ | -0.0134** | -0.0133** | -0.0161* | -0.0160* | -0.0174* | -0.0211* |
| | (0.00581) | (0.00580) | (0.00813) | (0.00805) | (0.00987) | (0.0112) |
| $ONI_{t-1} < 0$ | -0.00721 | -0.00693 | -0.00583 | -0.00558 | -0.00549 | -0.00545 |
| | (0.00512) | (0.00512) | (0.00787) | (0.00800) | (0.00896) | (0.0127) |
| $ONI_{t-1} \geq 0 \times SPEI_t$ | 0.0174*** | 0.0165** | 0.0186*** | 0.0188*** | 0.00631 | 0.00946 |
| | (0.00671) | (0.00685) | (0.00594) | (0.00591) | (0.0111) | (0.00885) |
| $ONI_{t-1} < 0 \times SPEI_t$ | 0.00824 | 0.00911 | 0.0106 | 0.0107 | -0.0218* | -0.0229** |
| | (0.00713) | (0.00732) | (0.00693) | (0.00685) | (0.0116) | (0.0106) |
| $ONI_{t+1} \geq 0$ | -0.0118** | -0.0121** | -0.0164*** | -0.0165*** | 0.000299 | -0.00424 |
| | (0.00541) | (0.00542) | (0.00473) | (0.00478) | (0.00886) | (0.00977) |
| $ONI_{t+1} < 0$ | -0.00151 | -0.00162 | -0.00338 | -0.00345 | 0.0108 | 0.0111 |
| | (0.00586) | (0.00585) | (0.00668) | (0.00668) | (0.0105) | (0.0121) |
| $SPEI_{t+1}$ | 0.00347 | 0.00361 | 0.00260 | 0.00388 | 0.000531 | 0.000872 |
| | (0.00215) | (0.00365) | (0.00207) | (0.00300) | (0.00340) | (0.00386) |
| $ONI_t \geq 0 \times SPEI_{t+1}$ | | -0.00394 | | -0.00549 | | |
| | | (0.00683) | | (0.00451) | | |
| $ONI_t < 0 \times SPEI_{t+1}$ | | 0.00412 | | 0.000737 | | |
| | | (0.00755) | | (0.00502) | | |
| Constant | 0.0270 | 0.0270 | 0.0341*** | 0.0340*** | 0.0272*** | 0.0282** |
| | (0.0172) | (0.0172) | (0.00708) | (0.00709) | (0.0101) | (0.0121) |
| Countries ($N$) | 39 | 39 | 39 | 39 | 36 | 36 |
| Observations ($N \times T$) | 1482 | 1482 | 1482 | 1482 | 1263 | 1263 |
| $R^2[within]$ | 0.115 | 0.116 | [0.0440] | [0.0445] | 0.0921 | [0.0519] |
| PSAR(1) | Yes | Yes | No | No | Yes | No |
| MA(3) | No | No | Yes | Yes | No | Yes |

*Note: Prais-Winsten (PSCE) estimates and fixed effects (within) regression models with Driscoll and Kraay (DK) standard errors. $ONI \geq 0$ and $ONI < 0$ stand respectively for El Niño and La Niña conditions. Standard errors are in parentheses. \*\*\*, \*\*, and \* indicate respectively 1%, 5%, and 10% significance levels. PSAR(1) stands for panel specific AR(1)-type autocorrelation. MA(3) denotes autocorrelation of the moving average type with automatic lag length.*

Table C.6: Including time-fixed effects

|  | Tropical & humid countries | | | Arid & temperate countries | | |
|---|---|---|---|---|---|---|
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| $ONI_t \geq 0$ | -0.0204*** | -0.0236*** | -0.0245*** | -0.0299** | -0.0311* | -0.0336*** |
|  | (0.0032) | (0.0002) | (0.0011) | (0.0146) | (0.0176) | (0.0114) |
| $ONI_t < 0$ | -0.0301*** | -0.0324*** | -0.0319*** | -0.0319** | -0.0281* | -0.0285*** |
|  | (0.0037) | (0.0005) | (0.0001) | (0.0130) | (0.0151) | (0.0012) |
| $SPEI_t$ |  | 0.0031 | -0.0038 |  | 0.0107*** | 0.0152*** |
|  |  | (0.0021) | (0.0037) |  | (0.0031) | (0.0054) |
| $ONI_{t-1} \geq 0$ |  |  | -0.0009 |  |  | -0.0224* |
|  |  |  | (0.0006) |  |  | (0.0134) |
| $ONI_{t-1} < 0$ |  |  | 0.0001 |  |  | -0.0029 |
|  |  |  | (0.0007) |  |  | (0.0154) |
| $ONI_{t-1} \geq 0 \times SPEI_t$ |  |  | 0.0185*** |  |  | 0.0052 |
|  |  |  | (0.0071) |  |  | (0.0099) |
| $ONI_{t-1} < 0 \times SPEI_t$ |  |  | 0.0090 |  |  | -0.0220** |
|  |  |  | (0.0073) |  |  | (0.0103) |
| Constant | 0.0347** | 0.0349*** | 0.0351*** | 0.0527*** | 0.0535*** | 0.0601*** |
|  | (0.0159) | (0.0122) | (0.0121) | (0.0154) | (0.0185) | (0.0077) |
| Countries ($N$) | 39 | 39 | 39 | 36 | 36 | 36 |
| Observations ($N \times T$) | 1521 | 1521 | 1521 | 1299 | 1299 | 1299 |
| $R^2$ | 0.1693 | 0.1472 | 0.1512 | 0.1544 | 0.1608 | 0.1684 |
| PSAR(1) | Yes | Yes | Yes | Yes | Yes | Yes |

*Note: Prais-Winsten (PSCE) estimates. $ONI \geq 0$ and $ONI < 0$ stand respectively for El Niño and La Niña conditions. Standard errors are in parentheses. ***, **, and * indicate respectively 1%, 5%, and 10% significance levels. PSAR(1) stands for panel specific AR(1)-type autocorrelation.*

Table C.7: Variance Inflation Factor (VIF) and Tolerance value (TOL)

|  | Tropical & humid countries | | | | Arid & temperate countries | | | |
|---|---|---|---|---|---|---|---|---|
|  | VIF | TOL | VIF | TOL | VIF | TOL | VIF | TOL |
| $ONI_t \geq 0$ | 1.42 | 0.703 | 59.22 | 0.02 | 1.40 | 0.72 | 58.82 | 0.02 |
| $ONI_t < 0$ | 1.38 | 0.72 | 137.5 | 0.01 | 1.39 | 0.72 | 137.6 | 0.01 |
| $SPEI_t$ | 3.33 | 0.30 | 3.51 | 0.28 | 3.43 | 0.29 | 3.67 | 0.27 |
| $ONI_{t-1} \geq 0$ | 1.40 | 0.71 | 49.29 | 0.02 | 1.40 | 0.71 | 49.18 | 0.02 |
| $ONI_{t-1} < 0$ | 1.48 | 0.68 | 15.45 | 0.06 | 1.47 | 0.68 | 15.45 | 0.06 |
| $ONI_{t-1} \geq 0 \times SPEI_t$ | 2.19 | 0.46 | 2.31 | 0.43 | 2.23 | 0.45 | 2.39 | 0.42 |
| $ONI_{t-1} < 0 \times SPEI_t$ | 2.06 | 0.49 | 2.17 | 0.46 | 2.21 | 0.45 | 2.36 | 0.42 |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | No | No | Yes | Yes | No | No |

*Note: A Variance Inflation Factors (VIF) superior to 10 and a Tolerance value (TOL) inferior to 0.2 indicate strong multicolinearity among regressors. $TOL = 1 - R_j^2$, where $R_j^2$ is the coefficient of determination from the regression of an independant variable j on all other independant variables.*